



Leveraging “Right Now”:

Concepts, Challenges, and Direction for Analytics on the Wire

S. Ryan Quick *@phaedo*,
Principal Architect
PayPal Advanced Technology Group

The Wire as a “Data Space”

“Play it where it lies...”

The Wire as a “Data Space”

... and the least-utilized at that.

- We’ve entered the Zetabyte Era of computing. 34.9TB/sec (1.1ZB/yr) in flight on the internet at any moment. —This is only a fraction of what’s moving on enterprise, scientific, academic, government networks as well.
- We understand in-situ, and are maturing at moving data to get there.
- But why wait? **The data is already there** — we just have a hard time leveraging it.

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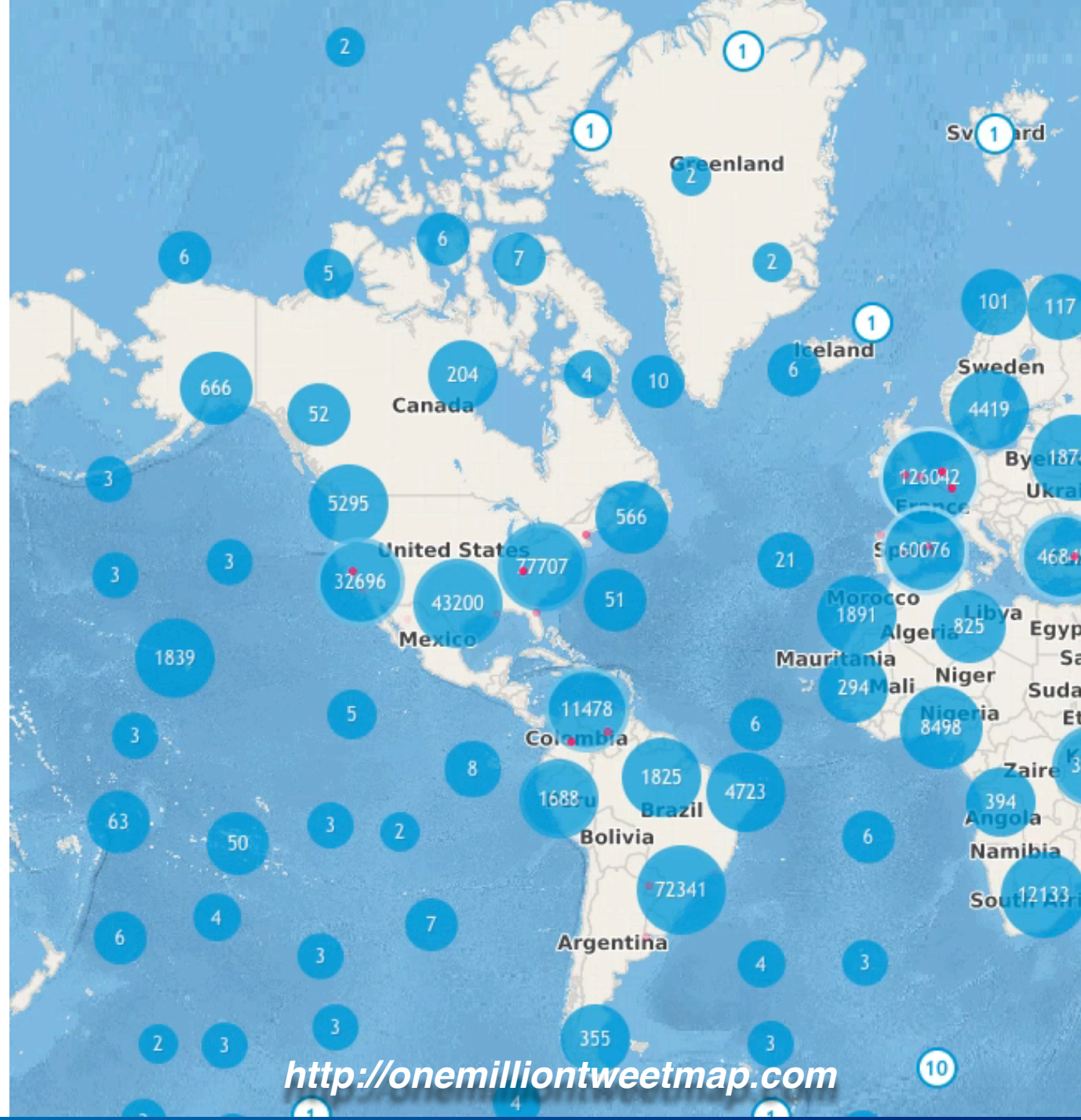


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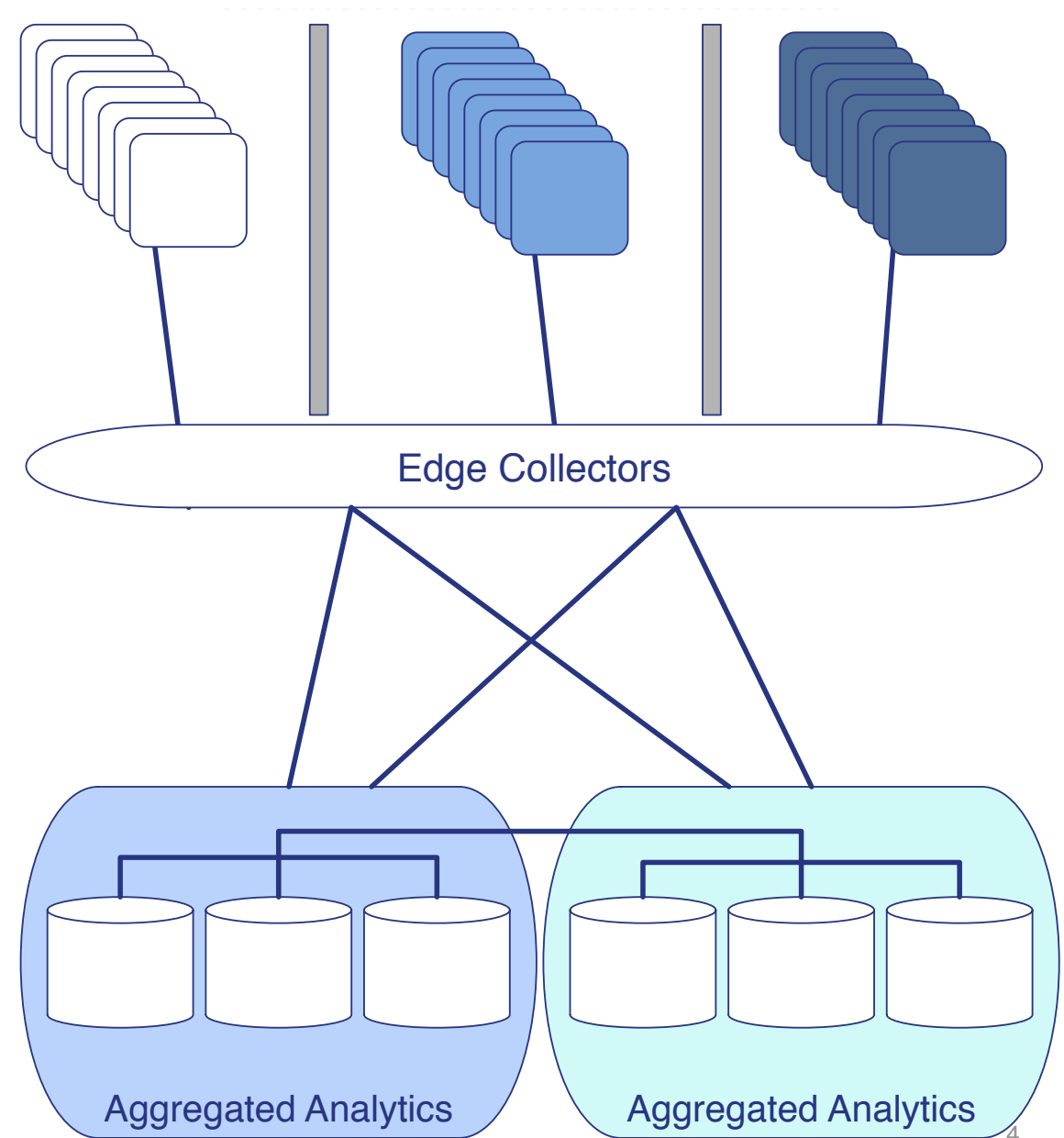
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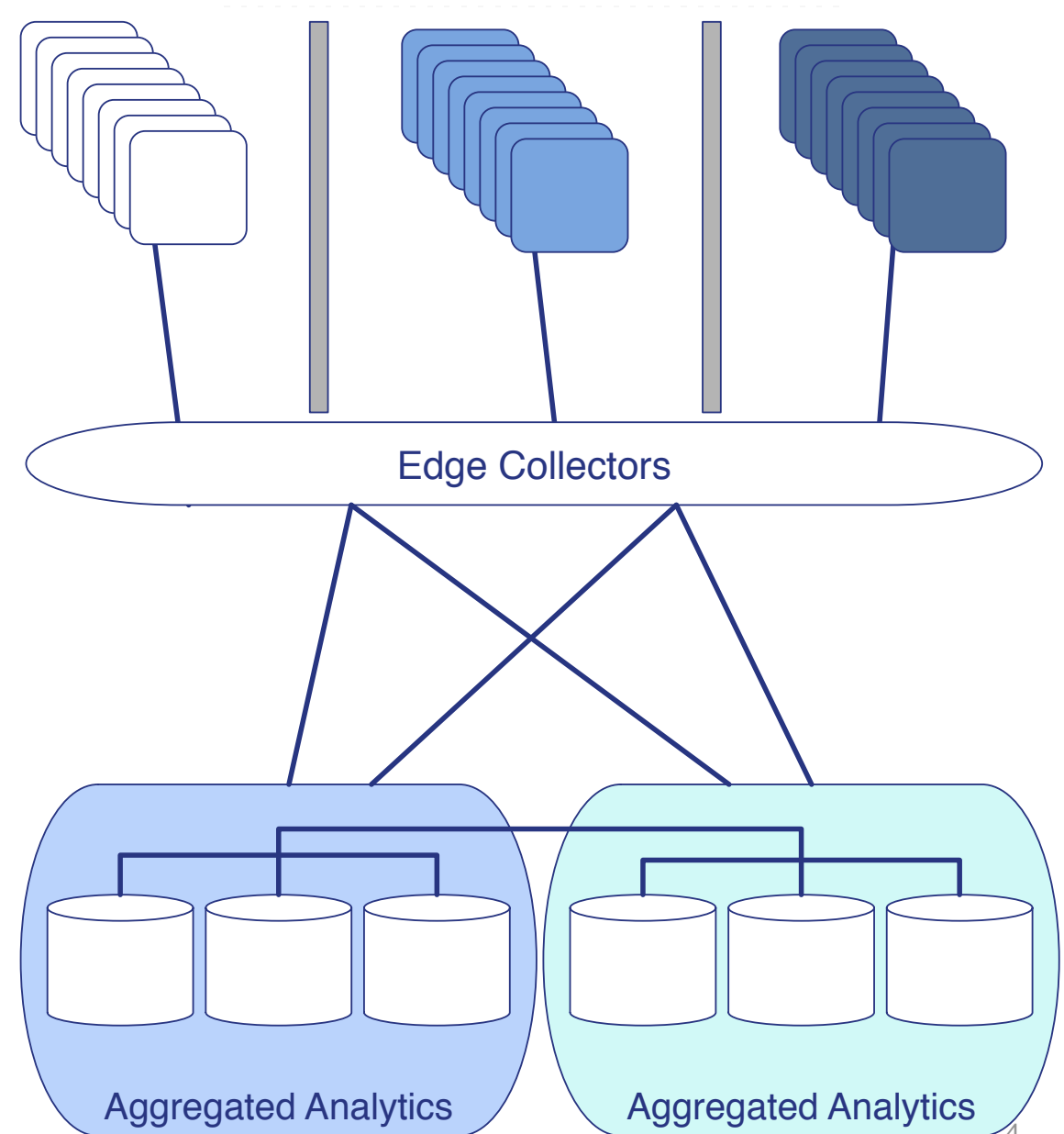
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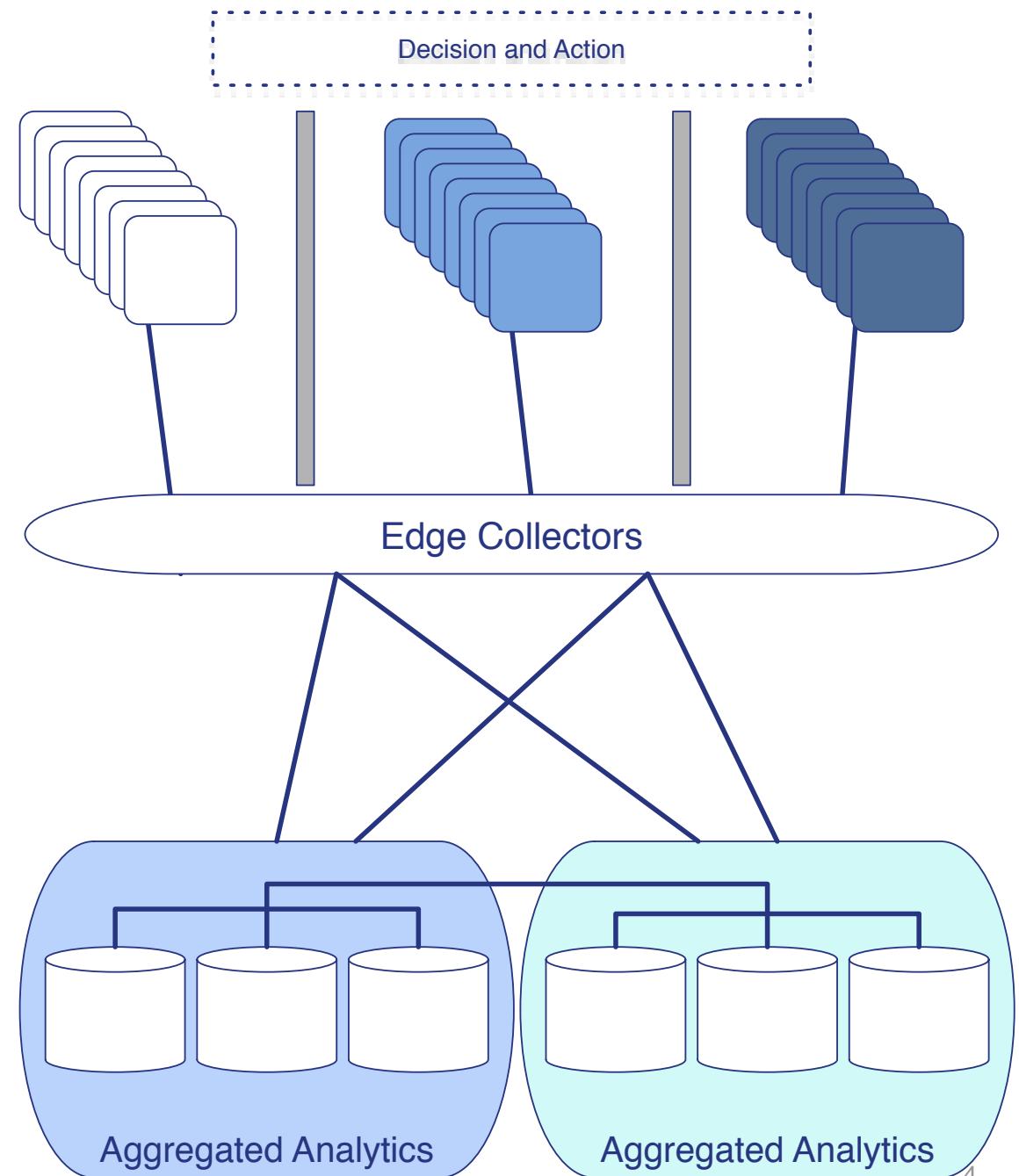
- Decisioning is fueled by information.
- As we grow more information from more sources informs better decisions — as long as we can actually handle the growth itself. That’s the crux of the problem.
- Current paradigm is to bring data to centralized systems for analysis.
- Analytic complexity directly relates to
 - distance (time, space),
 - size (atomic, chunk, overall), and
 - rate (bandwidth, throughput)



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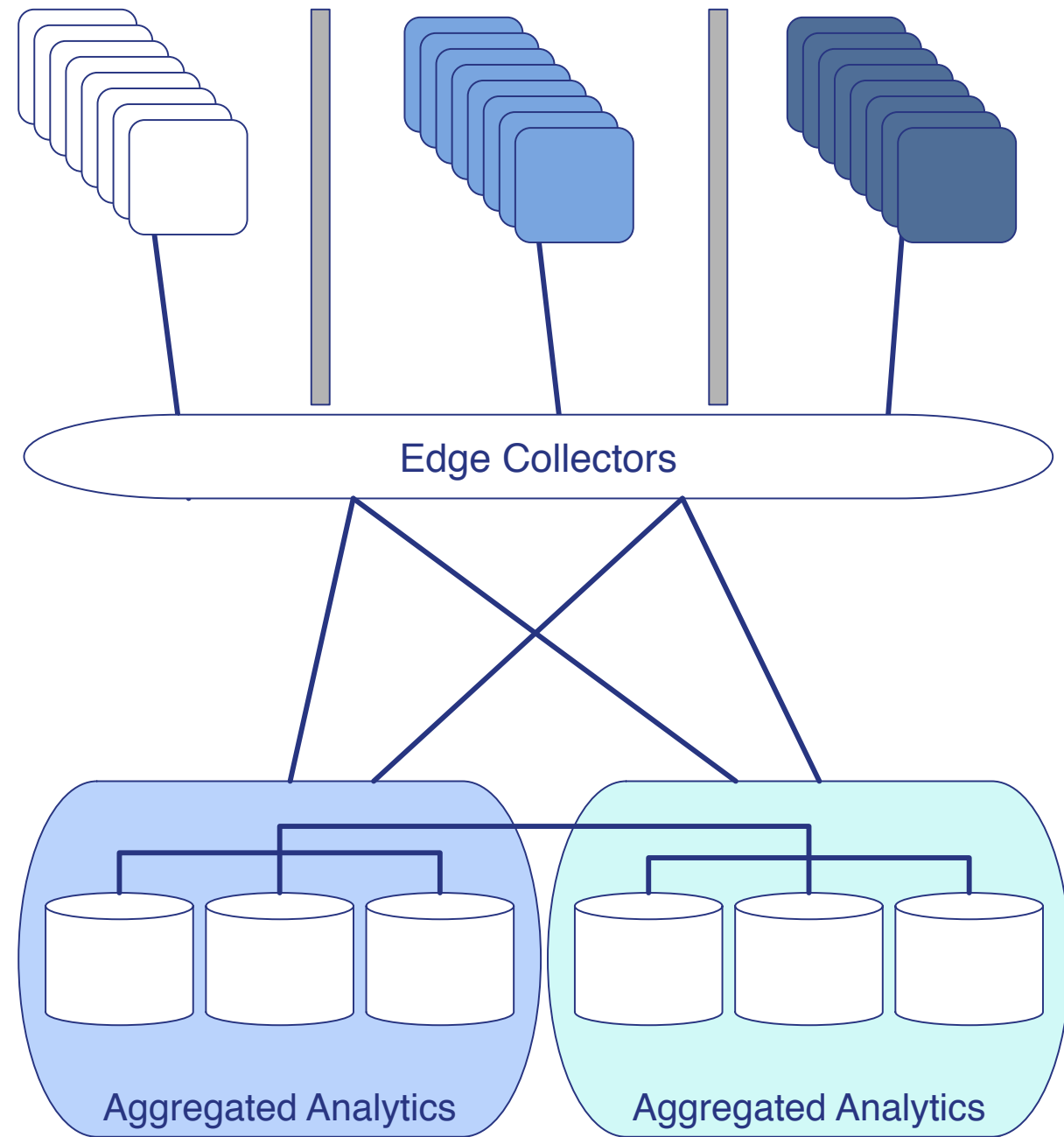
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- Analytic complexity directly relates to
 - distance (time, space),
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- Decisioning, Reaction, Prediction, etc. needed at the edge — ever-increasing demand for real-time action, which necessitates real-time insight.



The Wire as a “Data Space”

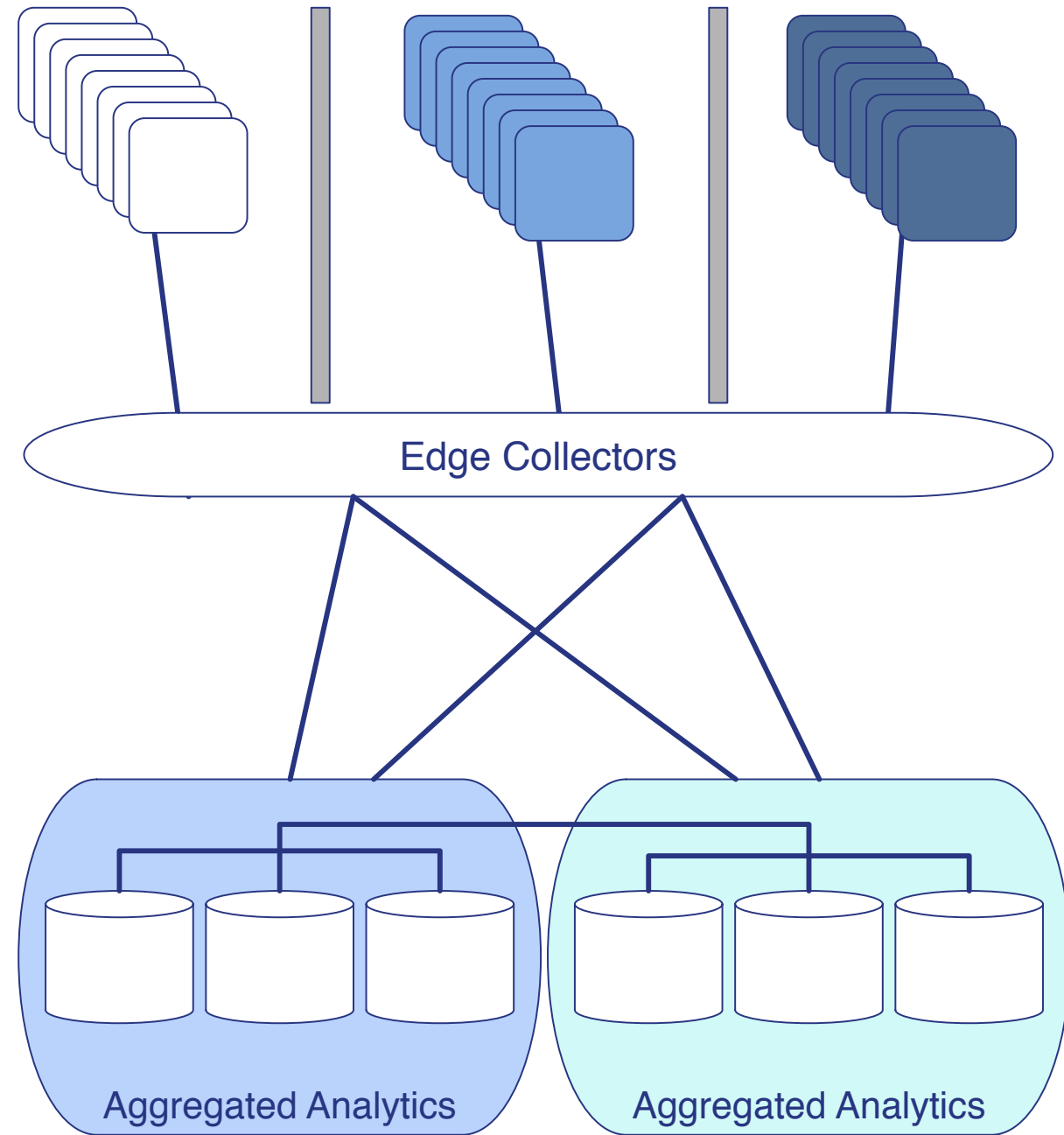
But wait! I Need All The Data!



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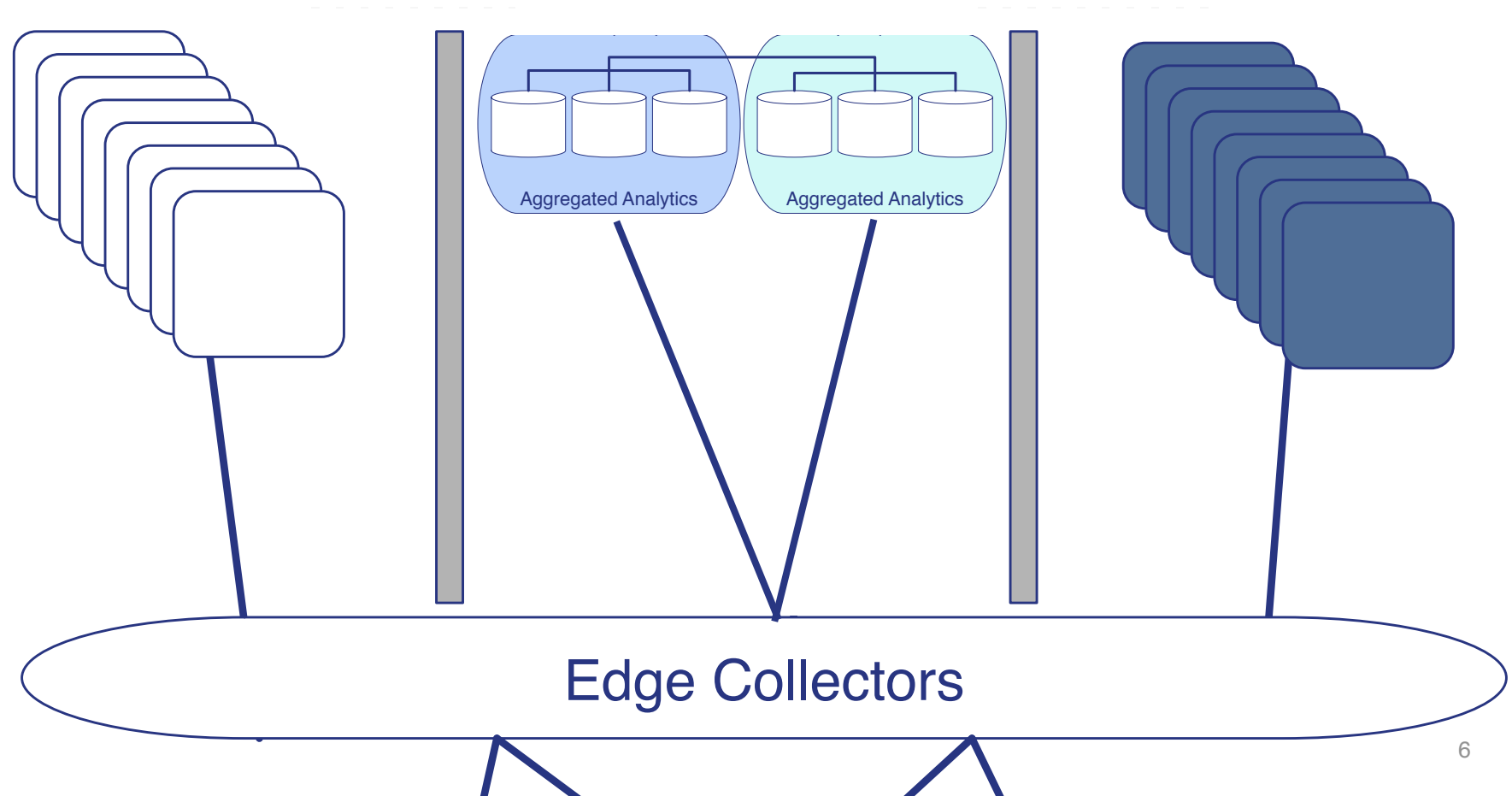
But wait! I Need All The Data!

- I need the entire dataset, from all sources, to derive information in the first place.
- My output is useful to me, but someone else will need all of the data to do their work as well.
- *(While I probably disagree, don't worry...)*



The Wire as a “Data Space”

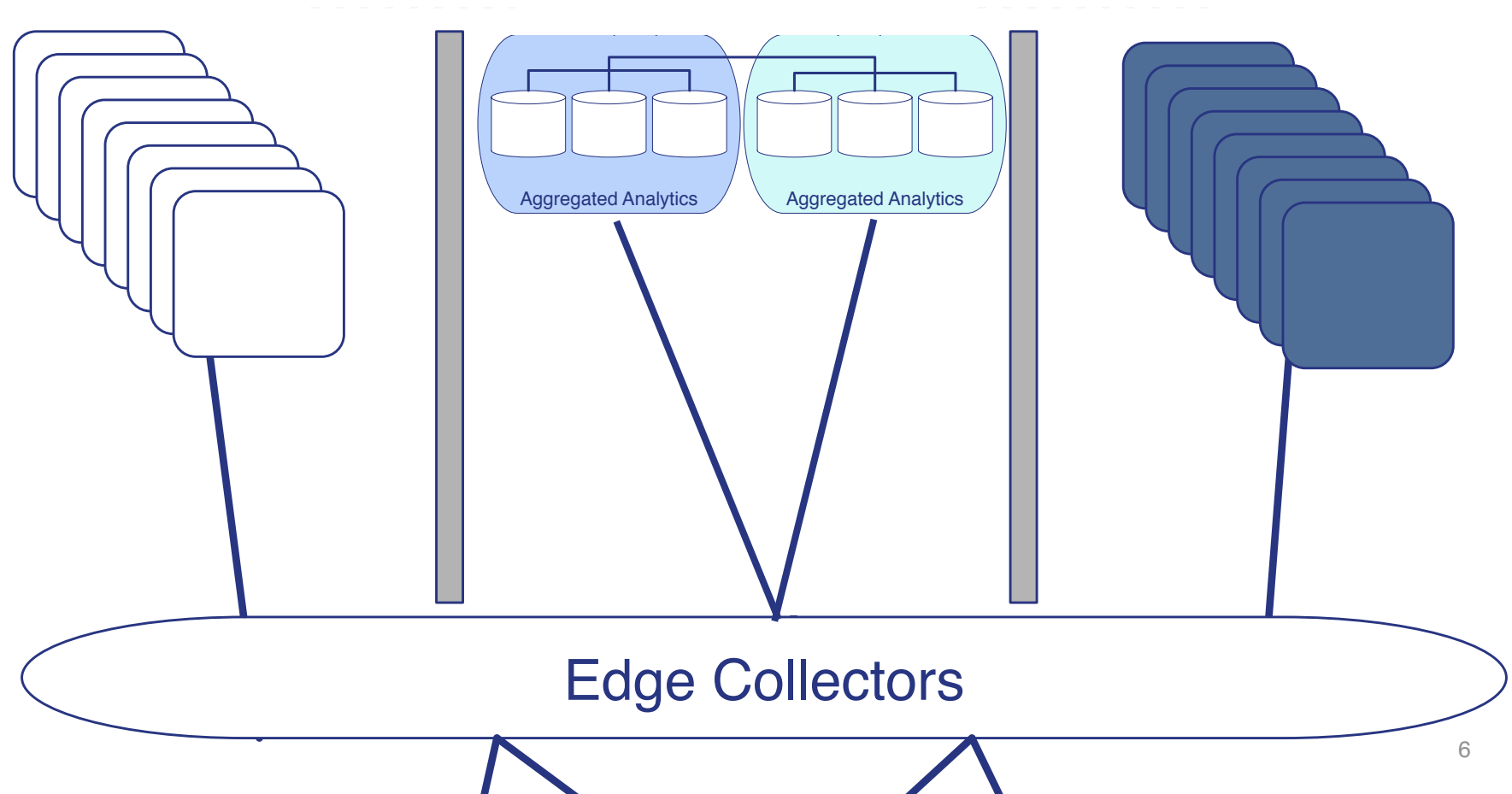
Output/Analysis is just another source...



The Wire as a “Data Space”

Output/Analysis is just another source...

- Sources can be simple, complex, small, or Big
- To leverage in-transit data, we must think beyond our use of content.
- Separate Insight from Information.
- Publish Everything.
- Let consumers consume.



Data Spaces

<i>in-situ</i> data at rest	<i>in-transit</i> data moving between endpoints	<i>in-transform</i> data under manipulation
Consistent Durable Accessible Atomic Ordered Structured (yes, even “unstructured data”)	Consistent* Transient*/Durable* Accessible Atomic*/Parallel* Ordered* Structured	Consistent* Transient/Durable* Accessible* Atomic Ordered Structured
Single data access Multichannel delivery*	Multichannel data access* Multichannel delivery*	Single data access† Single channel delivery
Commonly called “data at rest”	Data “in flight” or moving between endpoints	Data active manipulation (augmentation, transformation, reduction, format alteration, etc.)
* Configurable, depending on capability/need † This is changing w/ new hardware options/implementations		

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In-Transit Technology Concepts

“Sphere of Influence”: Transmission does not just relay information, but orders and gives meaning to it — increasing both insight and information itself.

In-Transit — Simple Technology Concepts

Data Sphere - 2014 Napa Earthquake

Time

- Ordering
 - (in-order, out-of-order, random, reverse, delayed)

Space

- Freshness
- Observational Distance
- Decay

Magnitude

- Object
- Information
- Data
- Relevance

In-Transit — Simple Technology Concepts

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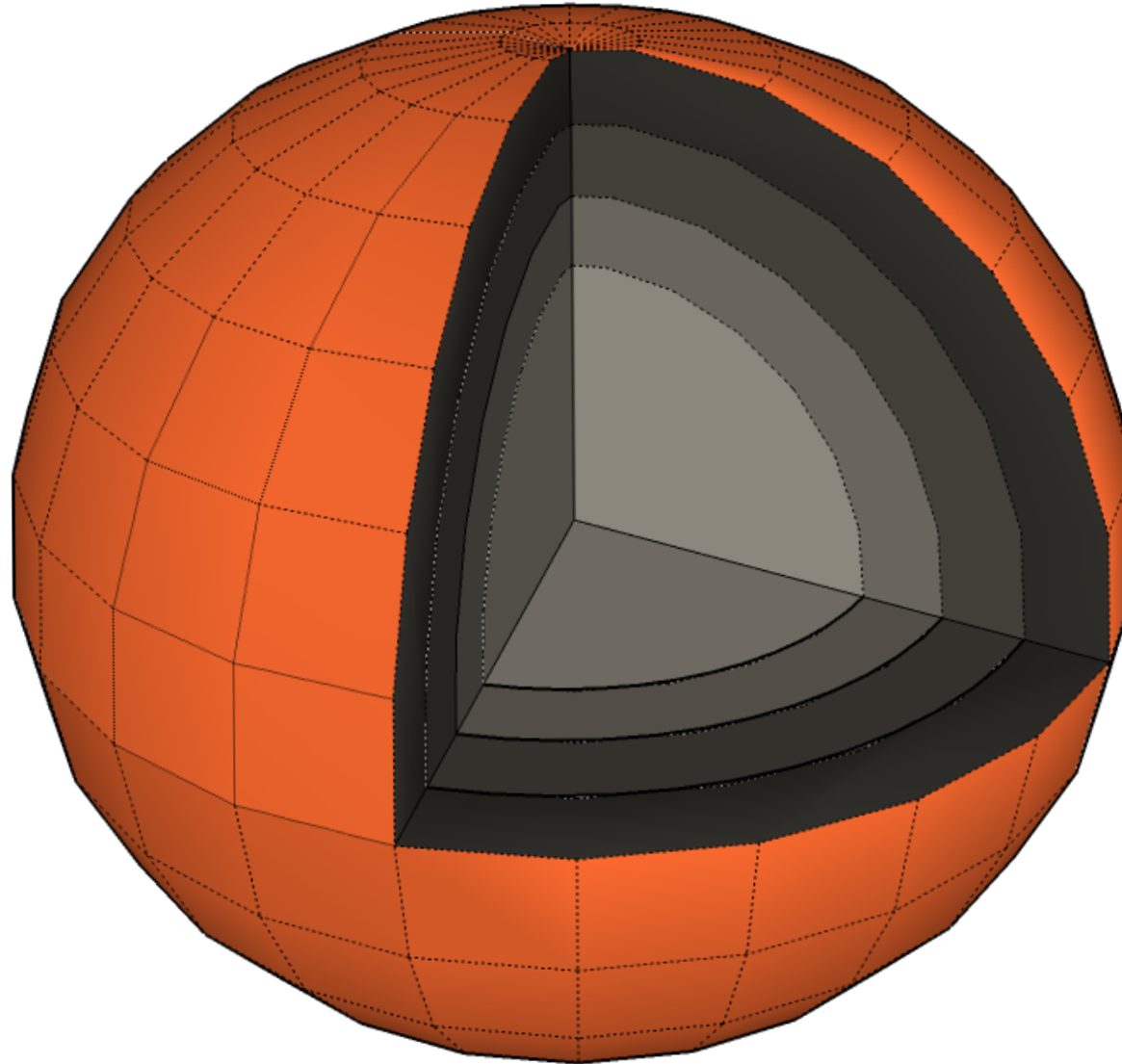
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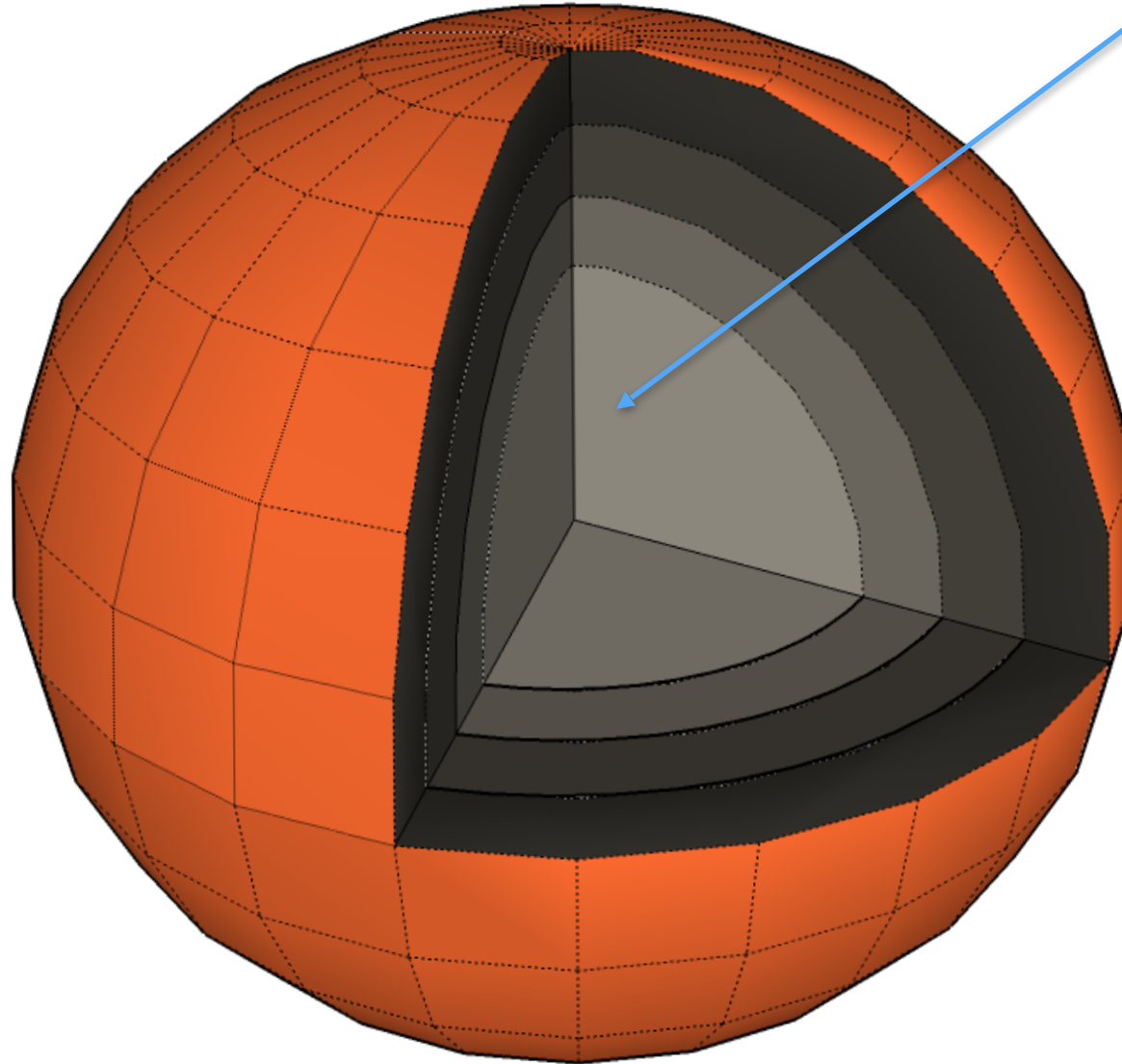
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T0



Earthquake initial event, no data

In-Transit — Simple Technology Concepts

Data Sphere - 2014 Napa Earthquake

Time

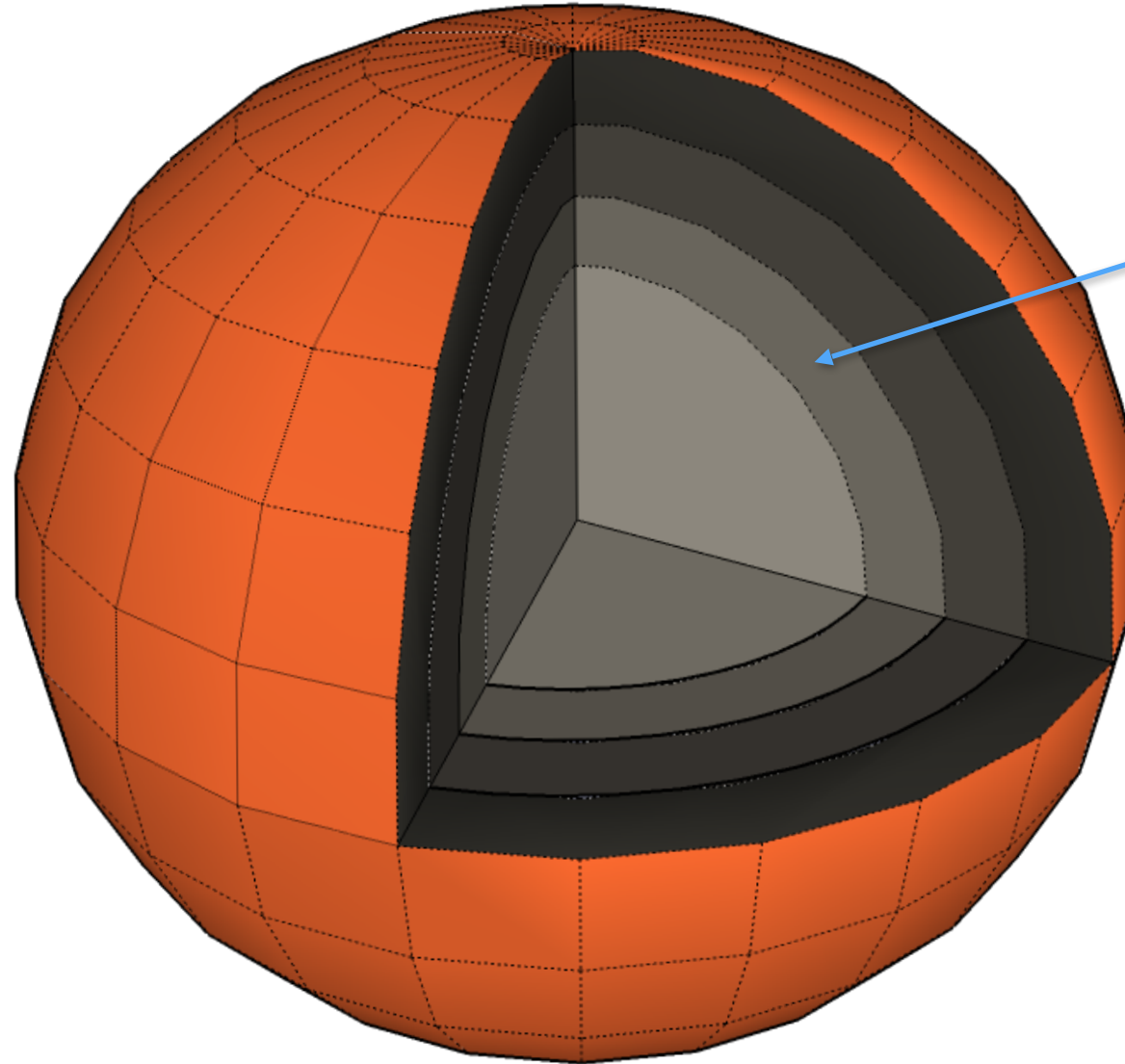
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T1



Seismometer,
initial data
generated about
event

In-Transit — Simple Technology Concepts

Data Sphere - 2014 Napa Earthquake

Time

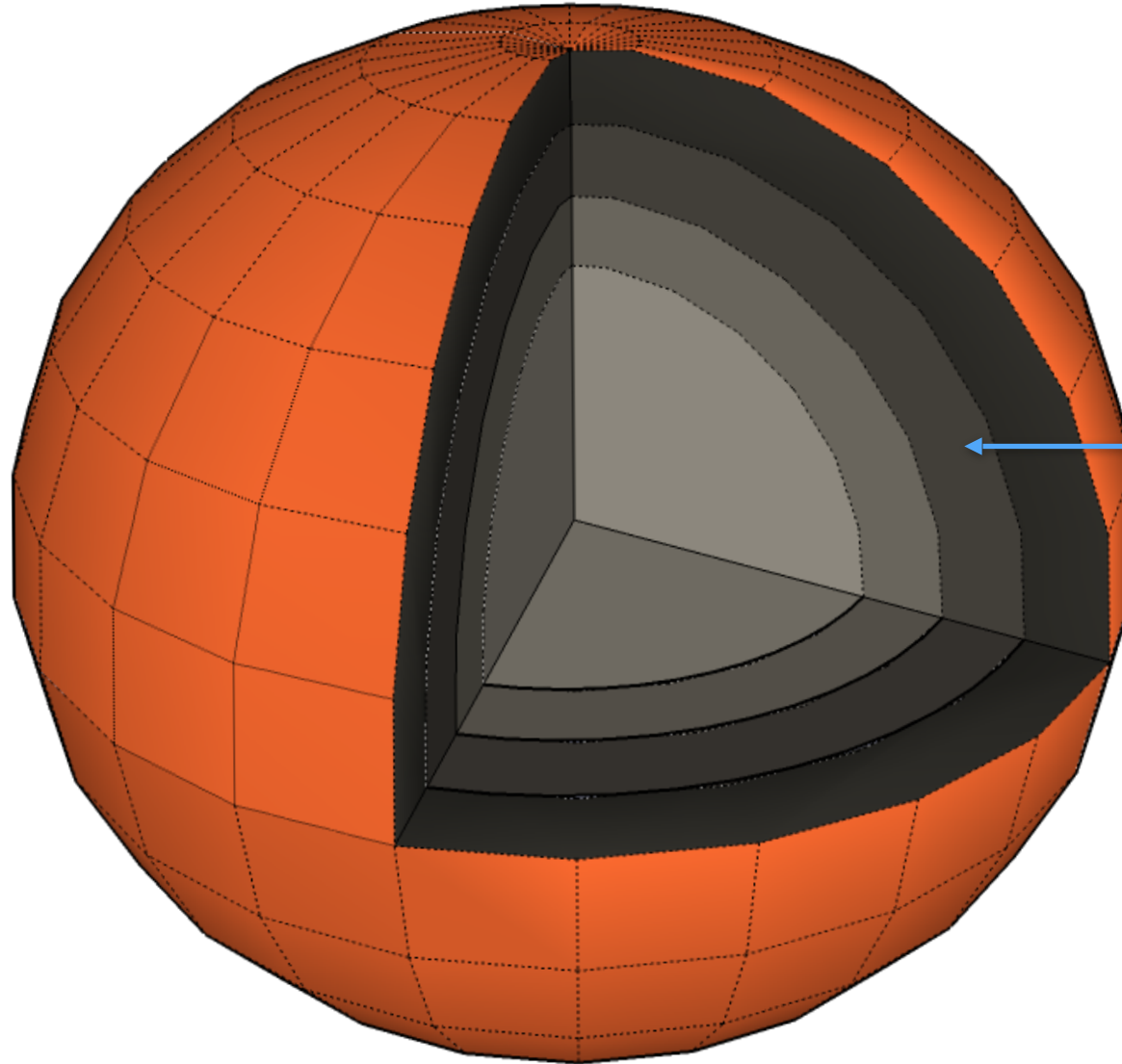
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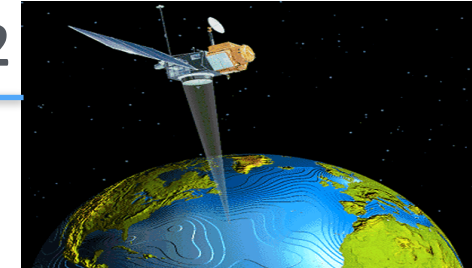
Magnitude

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Satellite Receiver
data transformed
to message

T2



In-Transit — Simple Technology Concepts

Data Sphere - 2014 Napa Earthquake

Time

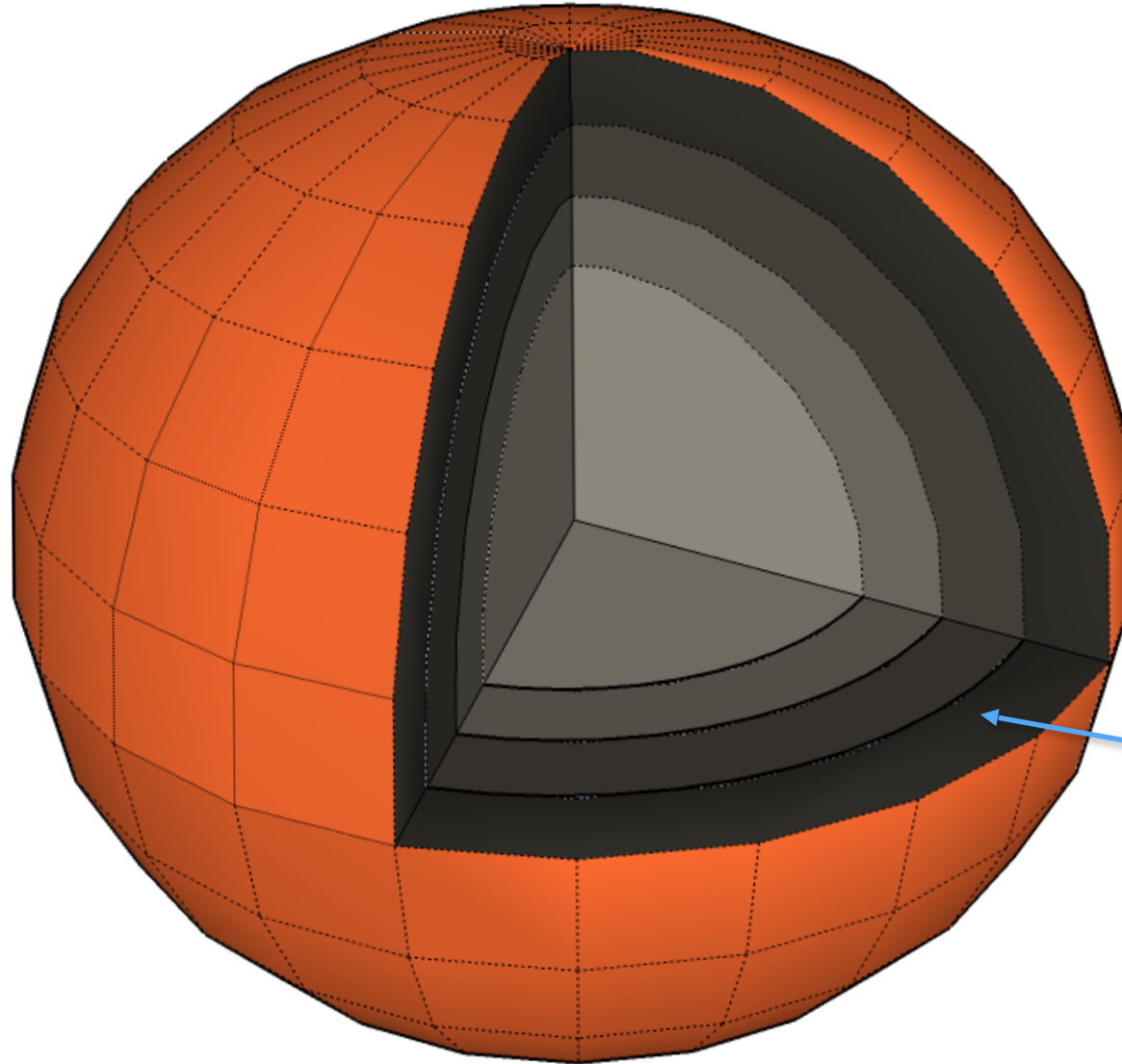
- Ordering
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Space

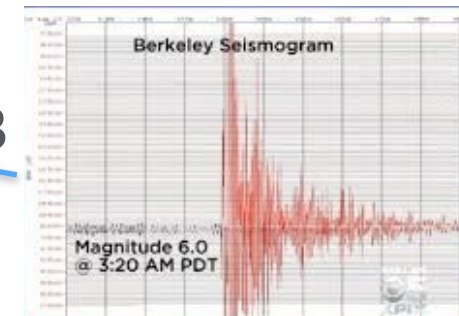
- Freshness
- Observational Distance
- Decay

Magnitude

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- Information
- Data
- Relevance



Ground station
reception
message
transformed to
human readable
format



In-Transit — Simple Technology Concepts

Data Sphere - 2014 Napa Earthquake

Time

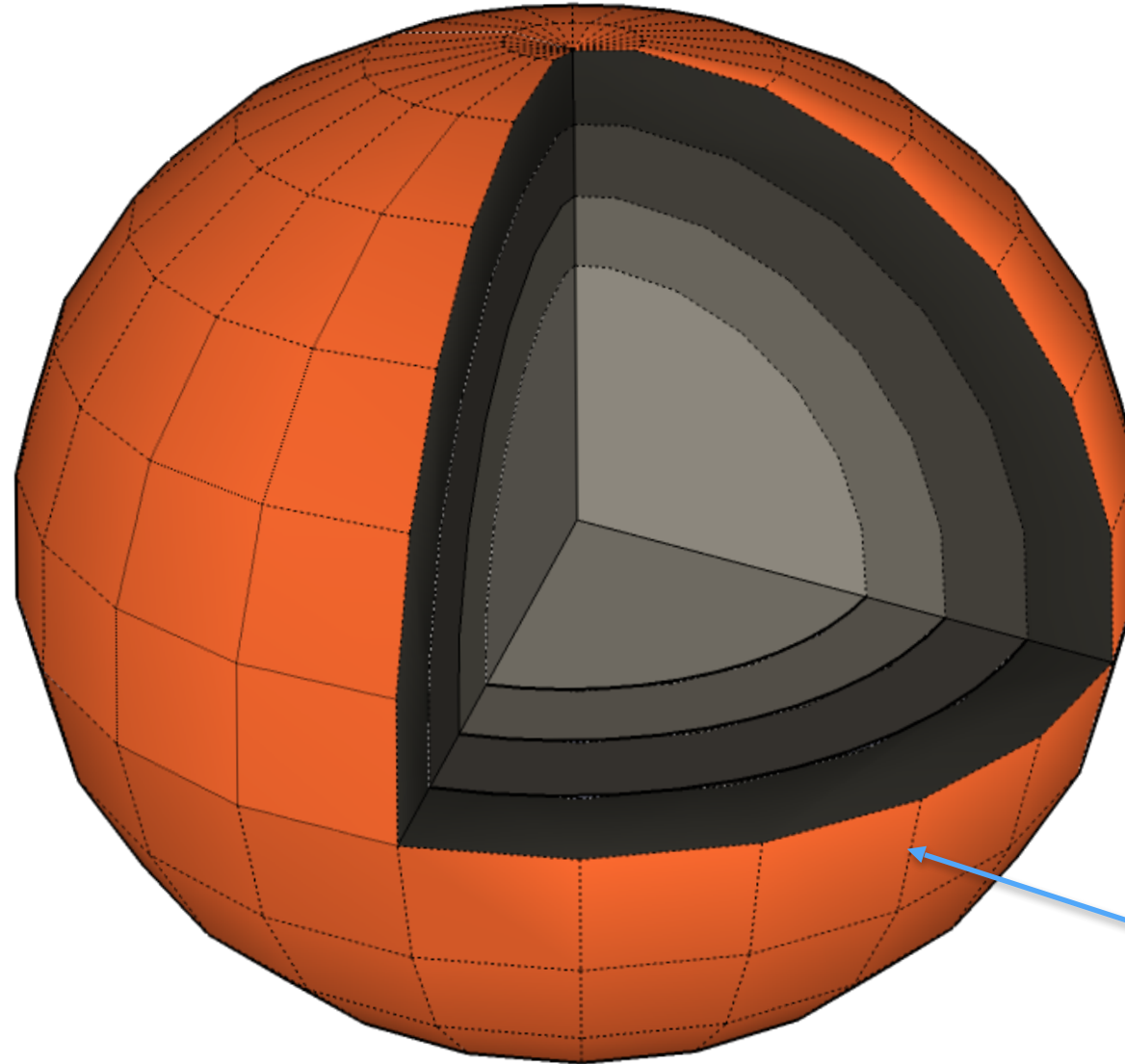
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Economic impact
post-event data

T4

Napa, Calif., earthquake:
Economic hit could reach \$1
billion
@phaedo

In-Transit — Simple Technology Concepts

Data Sphere - 2014 Napa Earthquake

Time

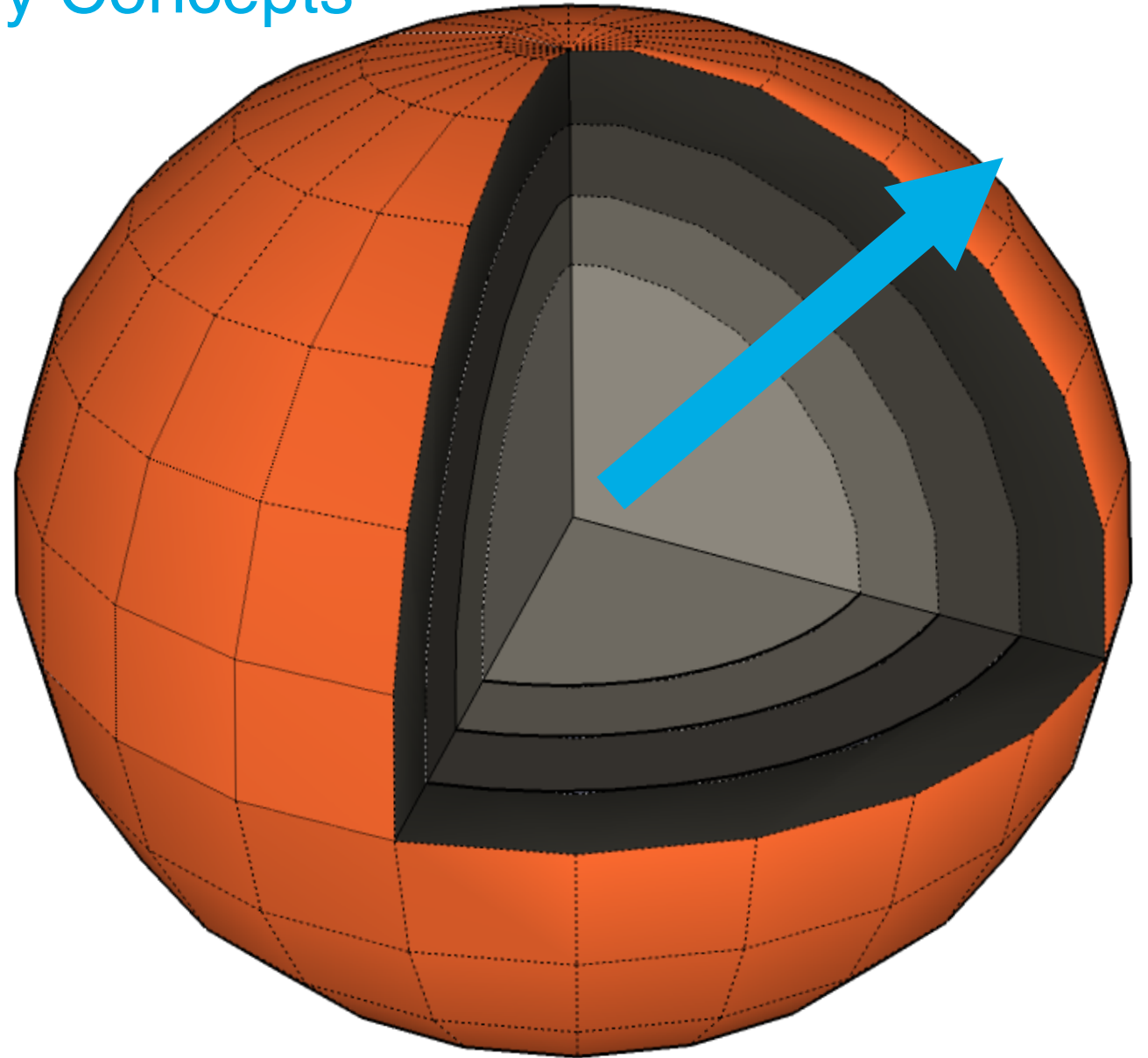
- **Ordering**
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In-Transit — Simple Technology Concepts

Data Sphere - 2014 Napa Earthquake

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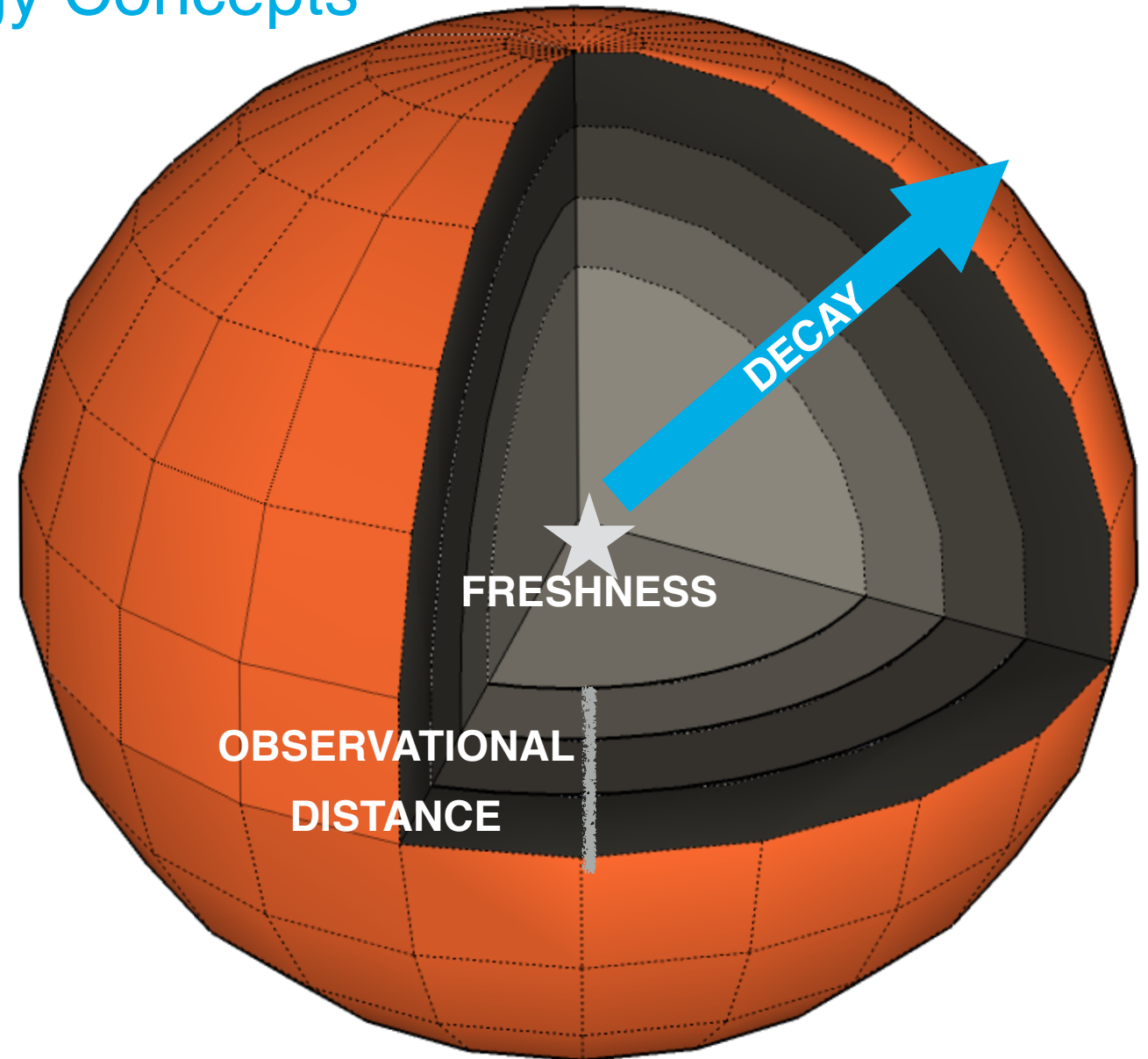
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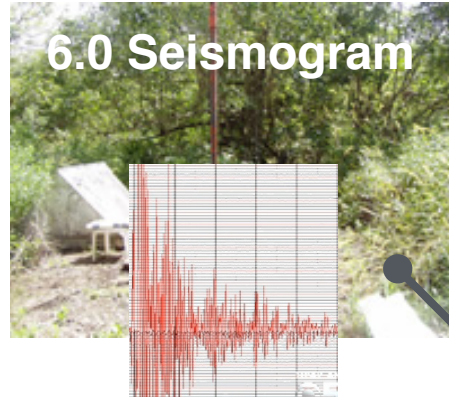
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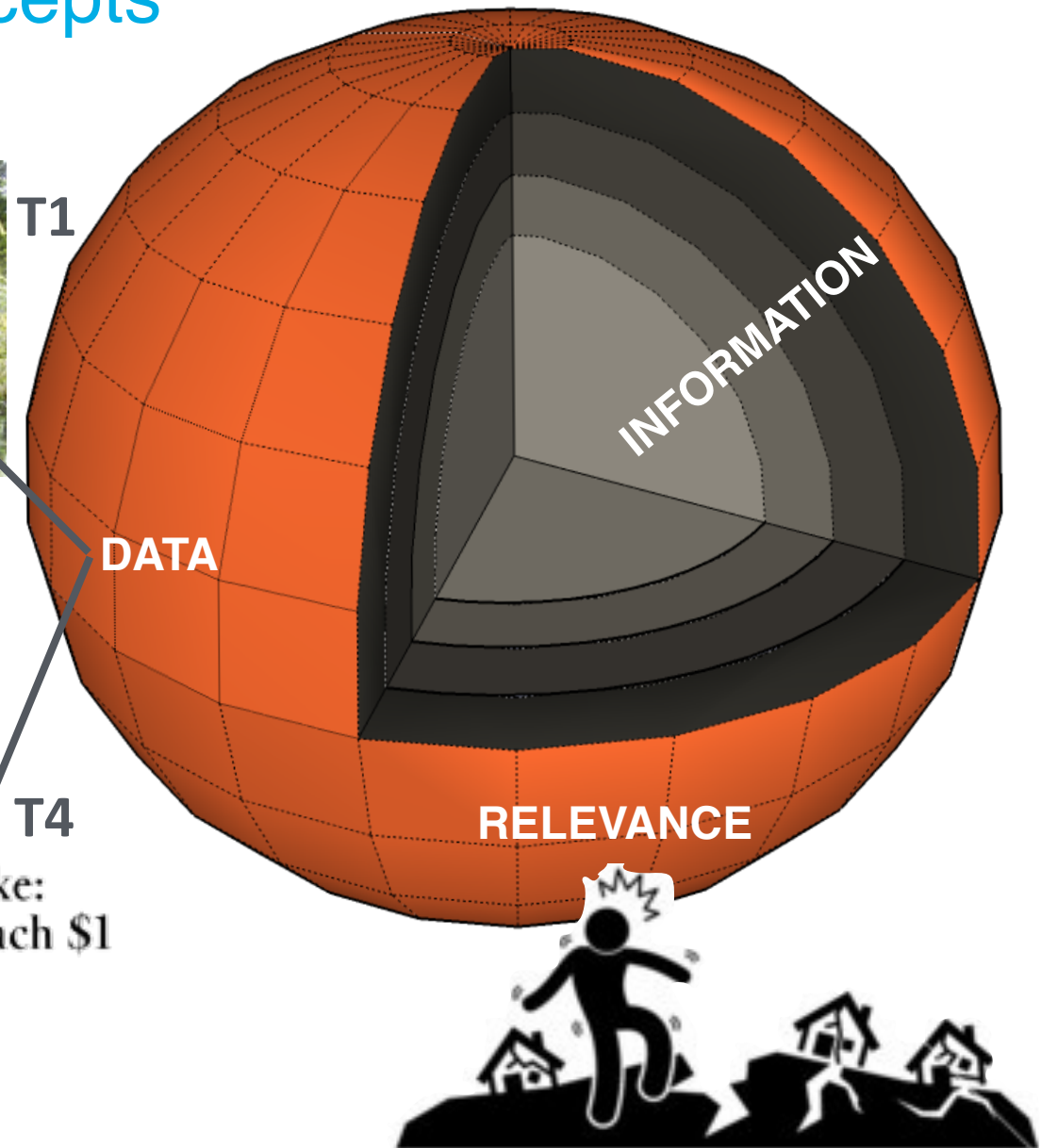


T1

DATA

T4

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In-Transit — Simple Technology Concepts

Data Sphere - 2014 Napa Earthquake

Repeatability

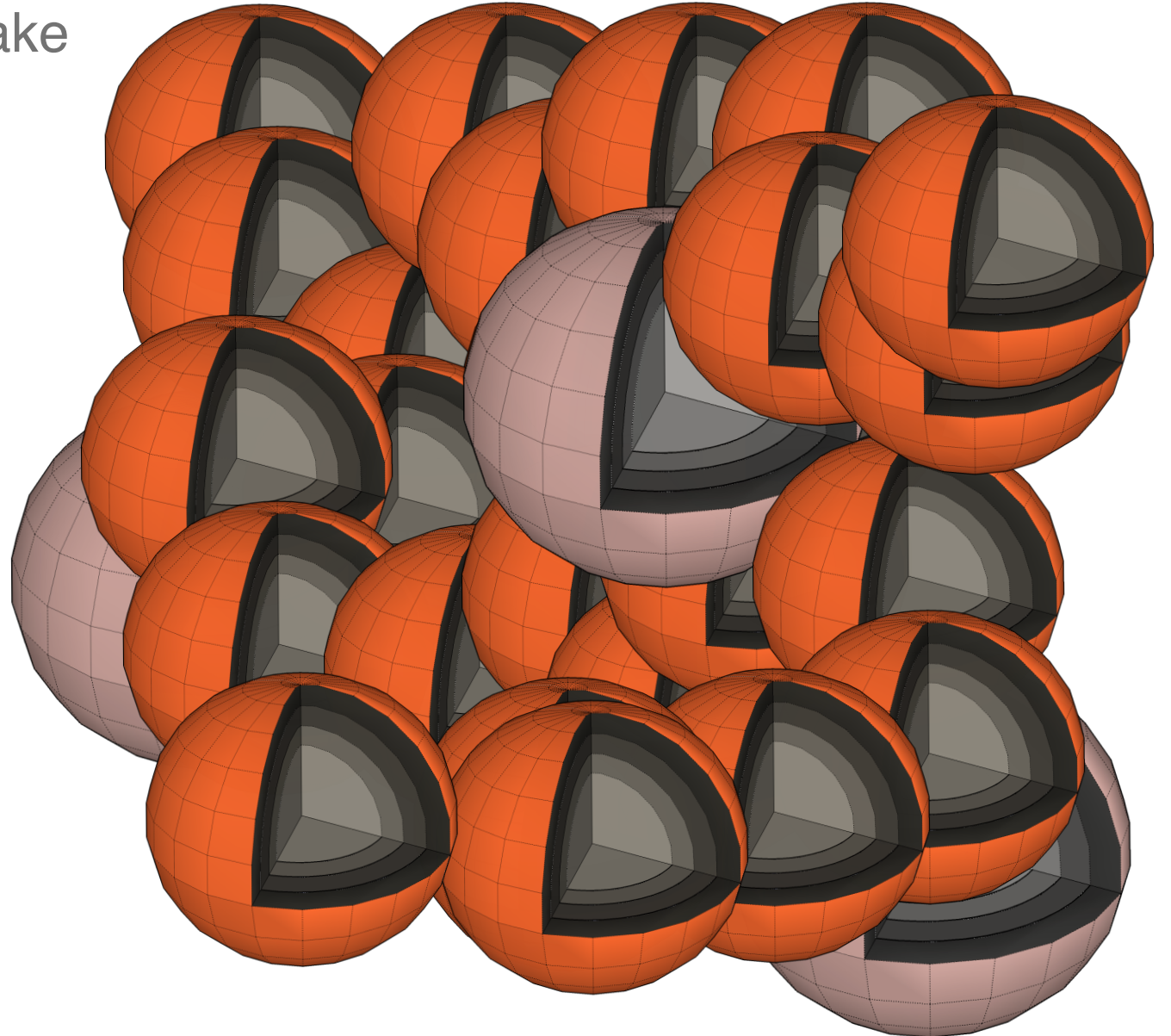
- Duplication
- Replication
- Uniqueness
- Similarity

Atomicity

- Influence
- Interdependency
- Discreteness

Longevity

- Persistence
- Retention
- Durability



In-Transit — Simple Technology Concepts

Data Sphere - 2014 Napa Earthquake

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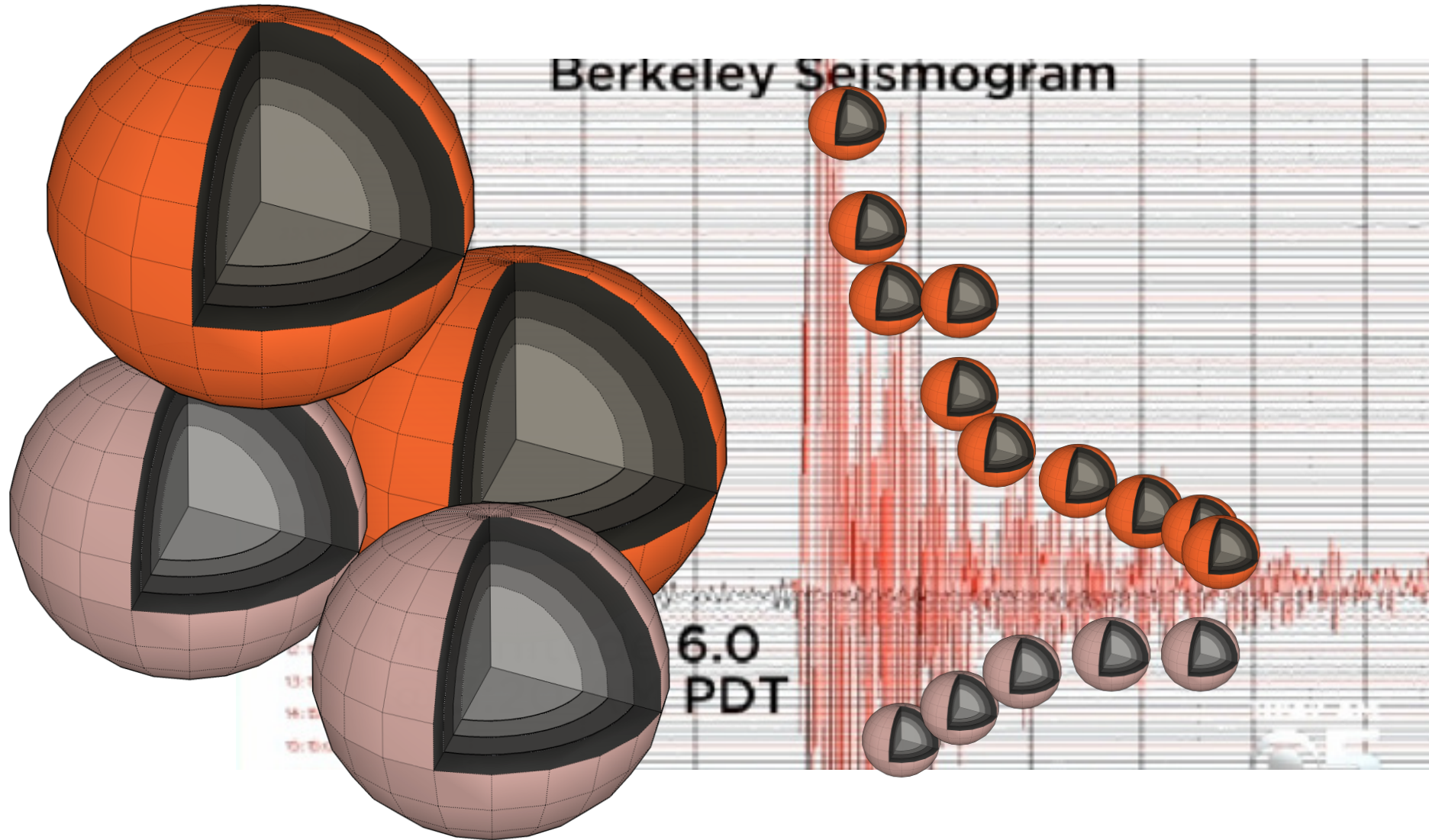
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Date	August 24, 2014
Origin time	10:20:44 UTC ^[1]
Magnitude	6.0 M_w ^[1]
Depth	7 mi (11 km) ^[1]
Epicenter	 38.22°N 122.31°W ^[1]
Fault	West Napa Fault
Type	Strike-slip ^[1]
Areas affected	North Bay (San Francisco Bay Area) California, United States
Total damage	\$362 million–\$1 billion ^{[2][3]}
Max. intensity	VIII (<i>Severe</i>) ^[1]
Casualties	1 killed ^[4] about 200 injured ^[5]



In-Transit — Simple Technology Concepts

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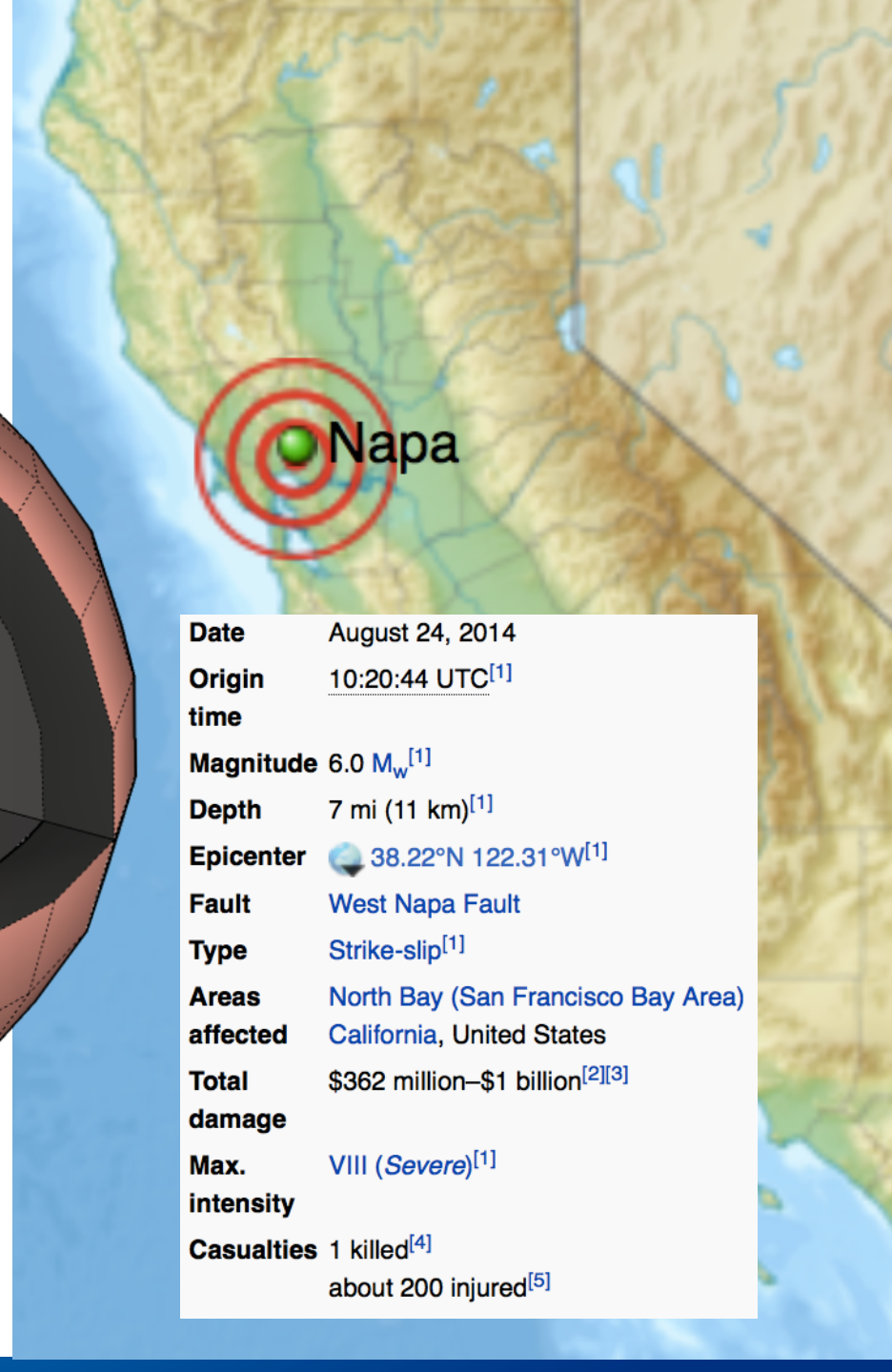
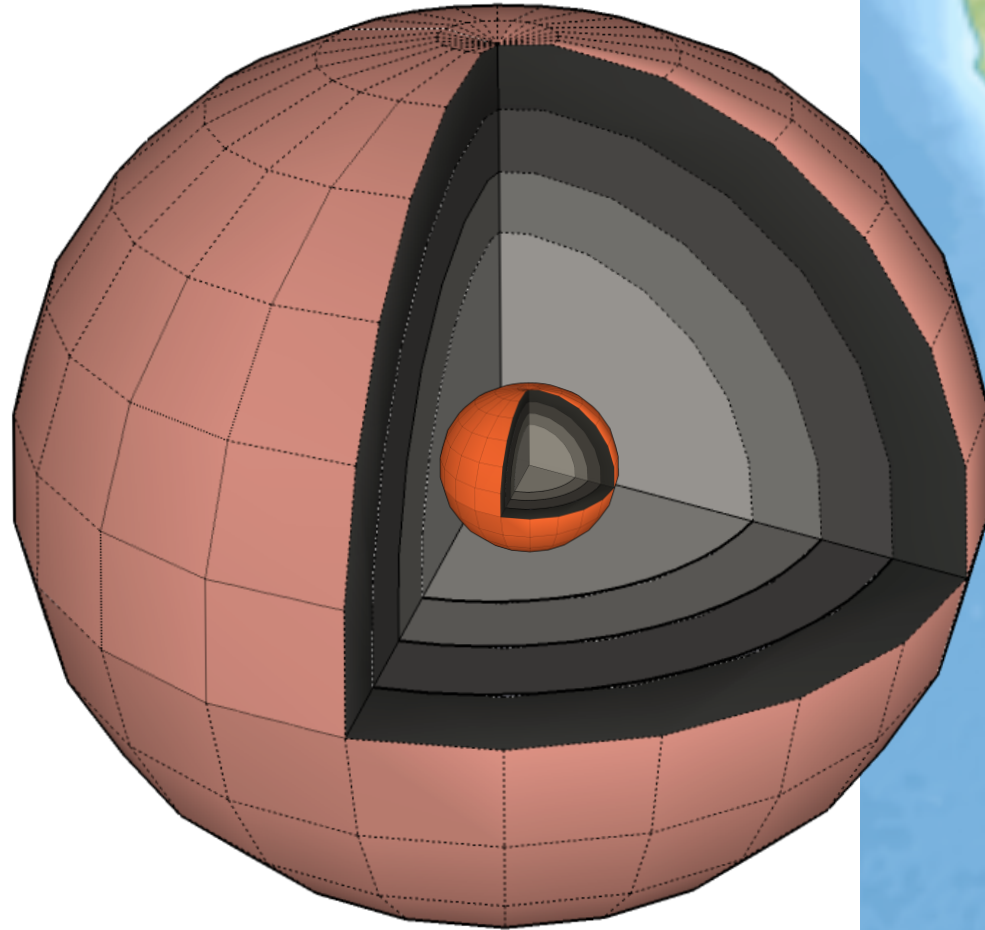
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In-Transit Technology Complex Concepts

leveraging simple concepts as building blocks

Compounded Dimensions and Series, Folded Dimensions and Series

Pattern Recognition

- Anomaly/Similarity Detection
- Frequency
- Magnitude
- Relative (Correlation/Negation/Absence)

State Change

- Event
- Observation
- Insight
- Data
- Request/Reply

In-Transit Technology Complex Concepts

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Stream Manipulation

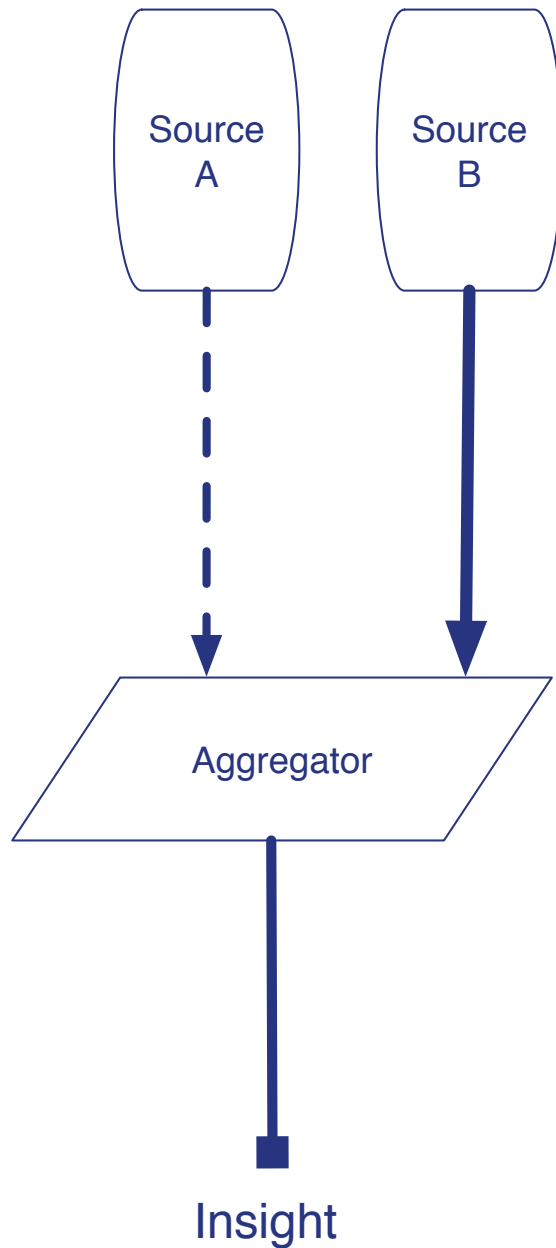
- Derivation
- Creation
- Replication
- Combination
- Views

Information and Insight

- Parallel Source
- Folded Source
- Source Augmentation

In-Transit Data Analytics Approaches

design patterns and sample use-cases



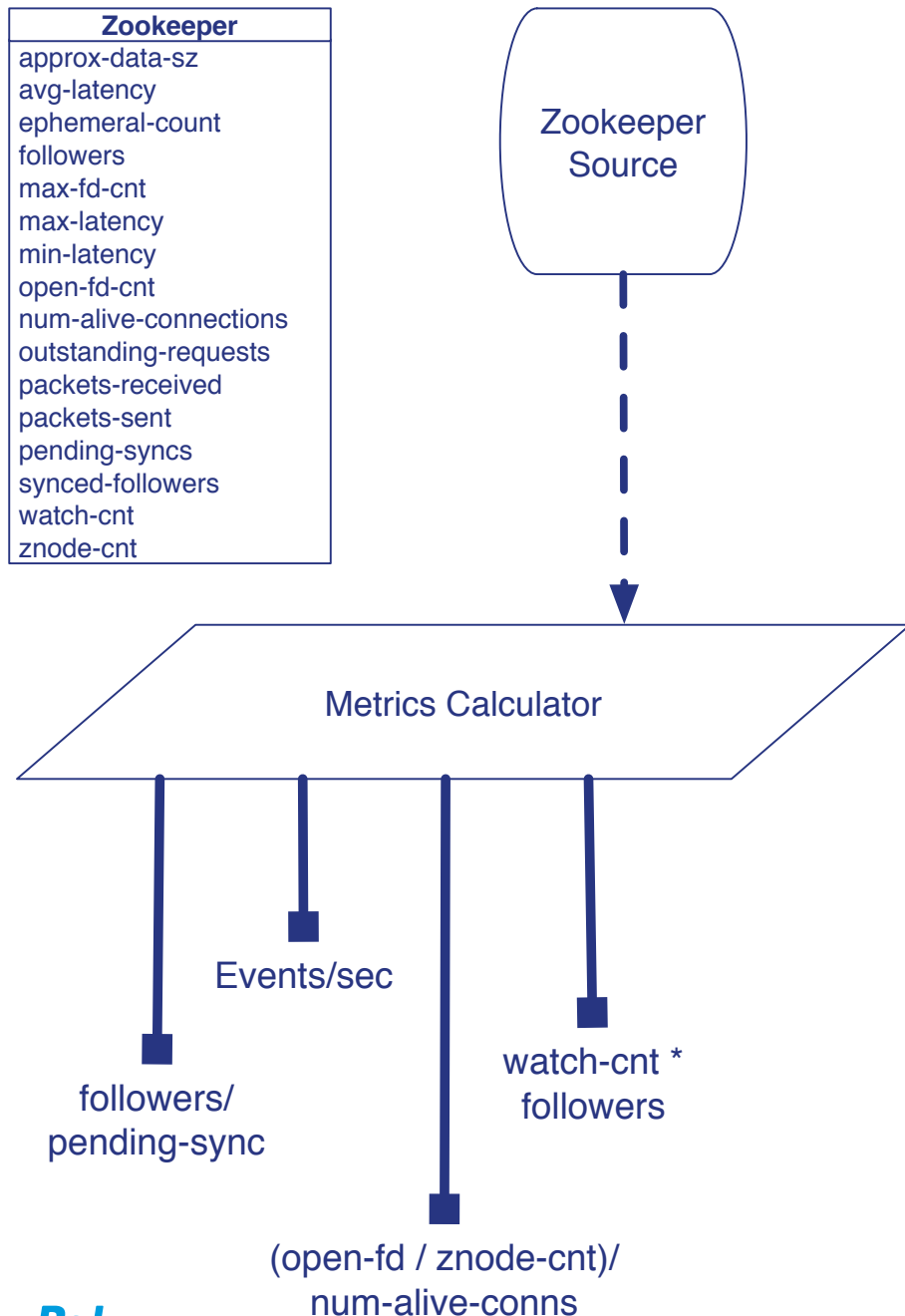
Simple Approaches

Aggregation

Event Statistics

Atomic Pattern Recognition

- Stream sources are combined in an aggregation application.
- Output is derived insight based on both sources
- **Use Case Example: CPU performance related to TCP Connections**
 - A: CPU idle % every 30s
 - B: TCP connections (incoming) [Event Driven]
 - INSIGHT: TCPCONNS/IDLE %



Simple Approaches

Aggregation

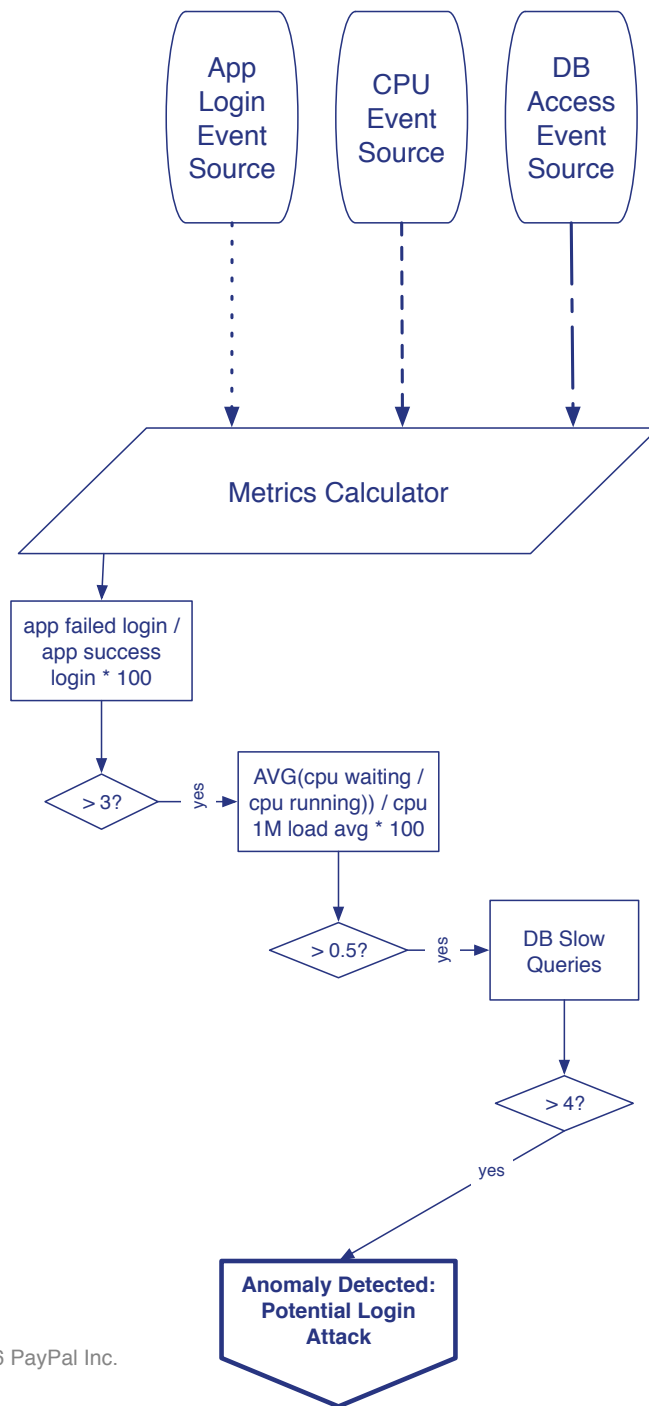
Event Statistics

Atomic Pattern Recognition

- Numerical/Categorical calculations based on data contained within the source datum/event
- Output insight effectively introduces new sources, generally numerical/gauged.
- **Use Case Example: Watched-Files-Per-Active-Consumer output as new stream source**
 - INSIGHT: *watch-cnt* (value per event) * *synced-followers* (value per event)

Available Source Fields

app login r/sec
app successful login r/sec
app failed login r/sec
cpu 1m load avg
cpu 5m load avg
cpu 15m load avg
cpu blocked proc cnt
cpu running proc cnt
cpu waiting proc cnt
cpu user %
cpu idle %
cpu system %
cpu io wait %
db active queries
db slow queries
db selects
db updates
db deletes
db rows fetched
db table locks held
db row locks held



Simple Approaches

Aggregation

Event Statistics

Atomic Pattern Recognition

- Simple thresholds within the event itself
- Correlation can be within a single source, or across disparate sources
- Represented as “waterfalling” but this depends on frequency and is really just easier for us to read, the operations are parallel and stateless (in this approach)
- **Use Case Example: Output Potential-Login-Attack events**

Compound Approaches

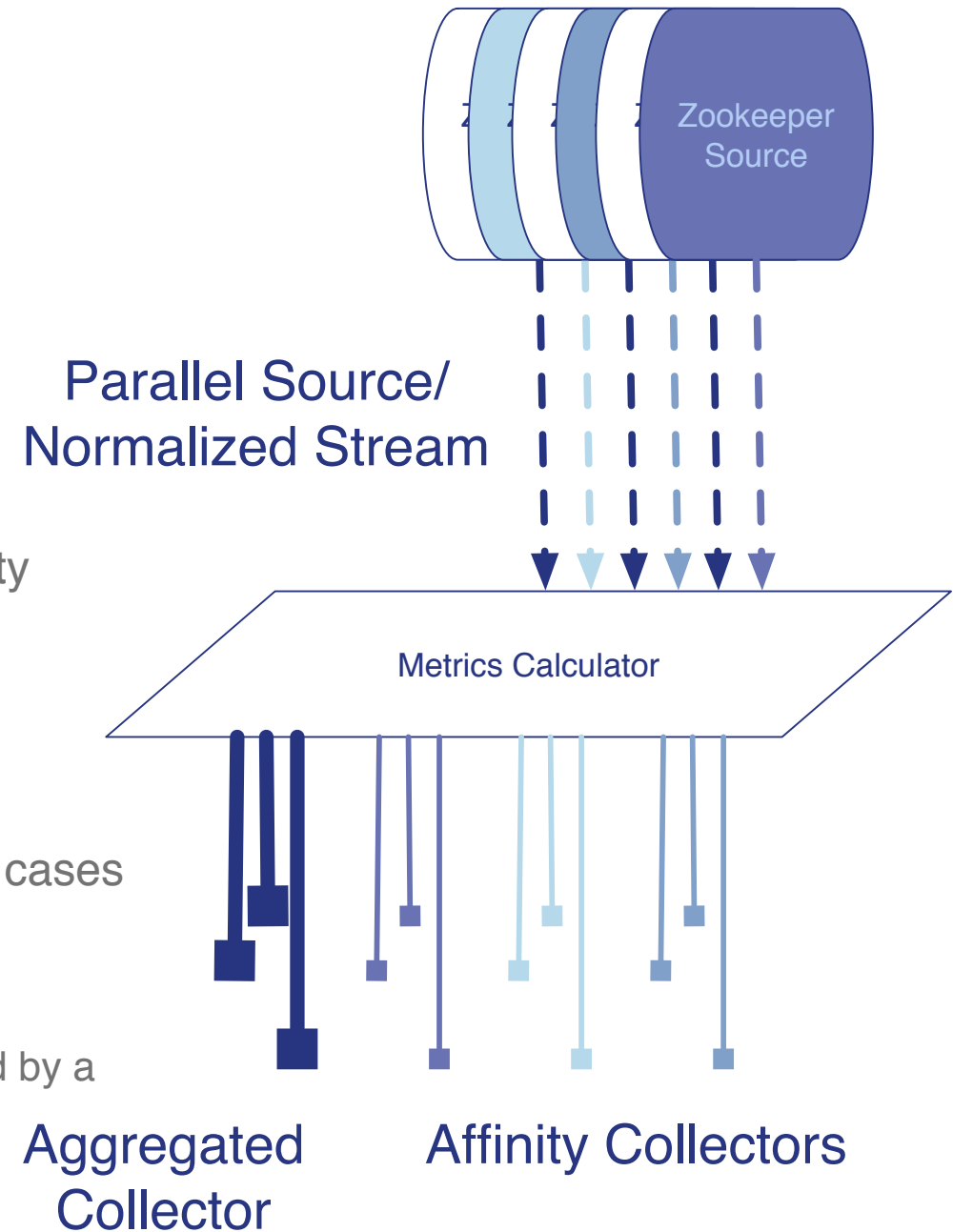
Affinity + Simple Case

Stream + Augmented Datasource

Parallel Stream

Frequency-Shifted Stream

- Given parallel publishers for single source schemas, affinity refers to collating events by
 - publisher
 - schema
 - both
- Can be implemented automatically based on other simple cases
- Use Case Example: “Person of Interest”, “Behavior of Interest”**
 - Collate data by publisher once an anomalous event is triggered by a simple approach
 - Collate all like-schema sources to watch “pool behavior”



Compound Approaches

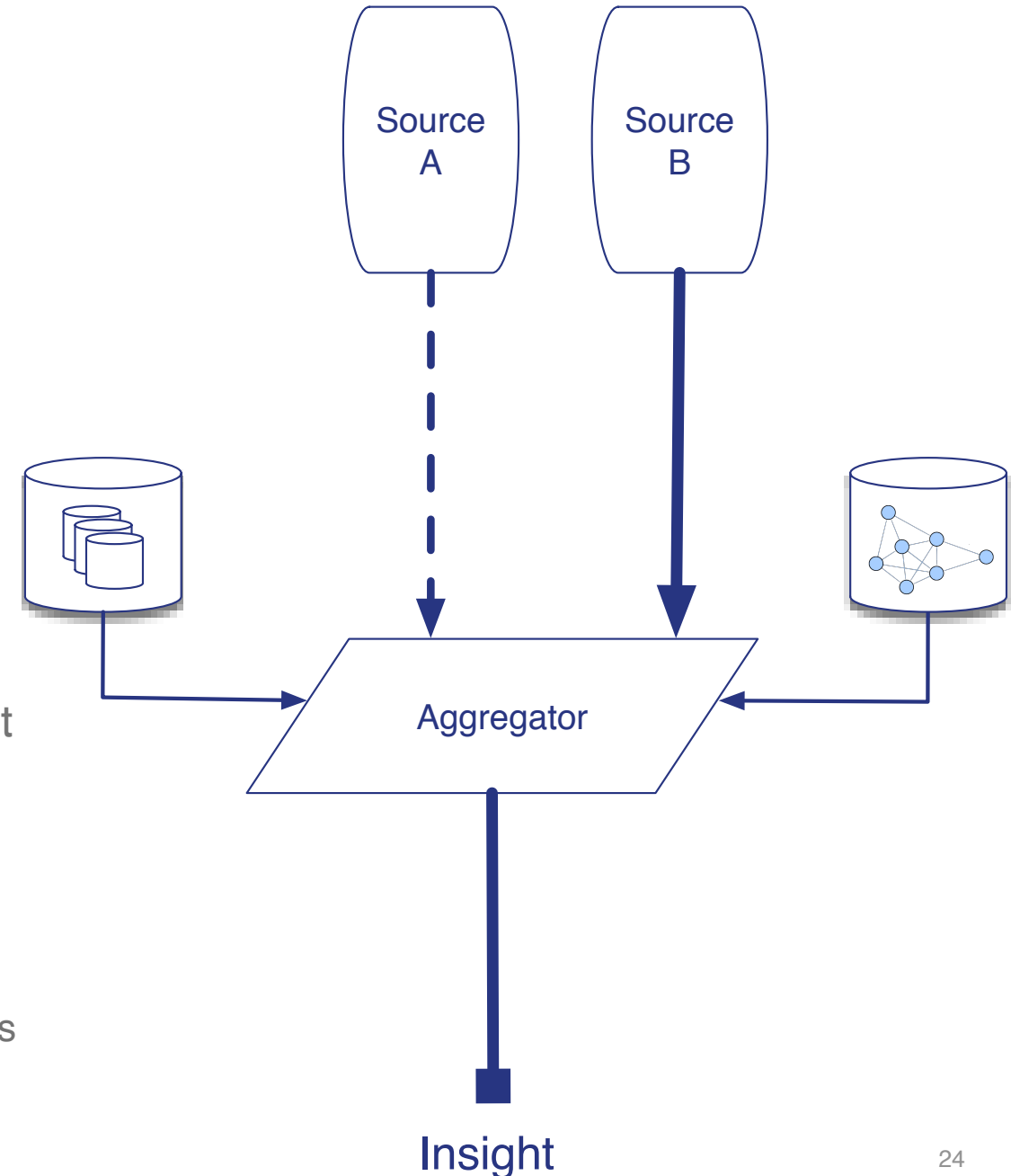
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Parallel Stream

Frequency-Shifted Stream

- Source data is augmented by
 - additional sources (alternate schema)
 - additional data sources (RDBMS, GraphDB, KV, Cache, etc)
- Used in cases where information on the wire requires additional context, culling, augmentation to provide insight
- **Use Case Example: Network Detection**
 - Event Source provides transaction details, network actors
 - RDBMS provides known-network attributes
 - Graph DB provides existing actor-network
 - Aggregator determines similarity score that the current event is a particular network type



Compound Approaches

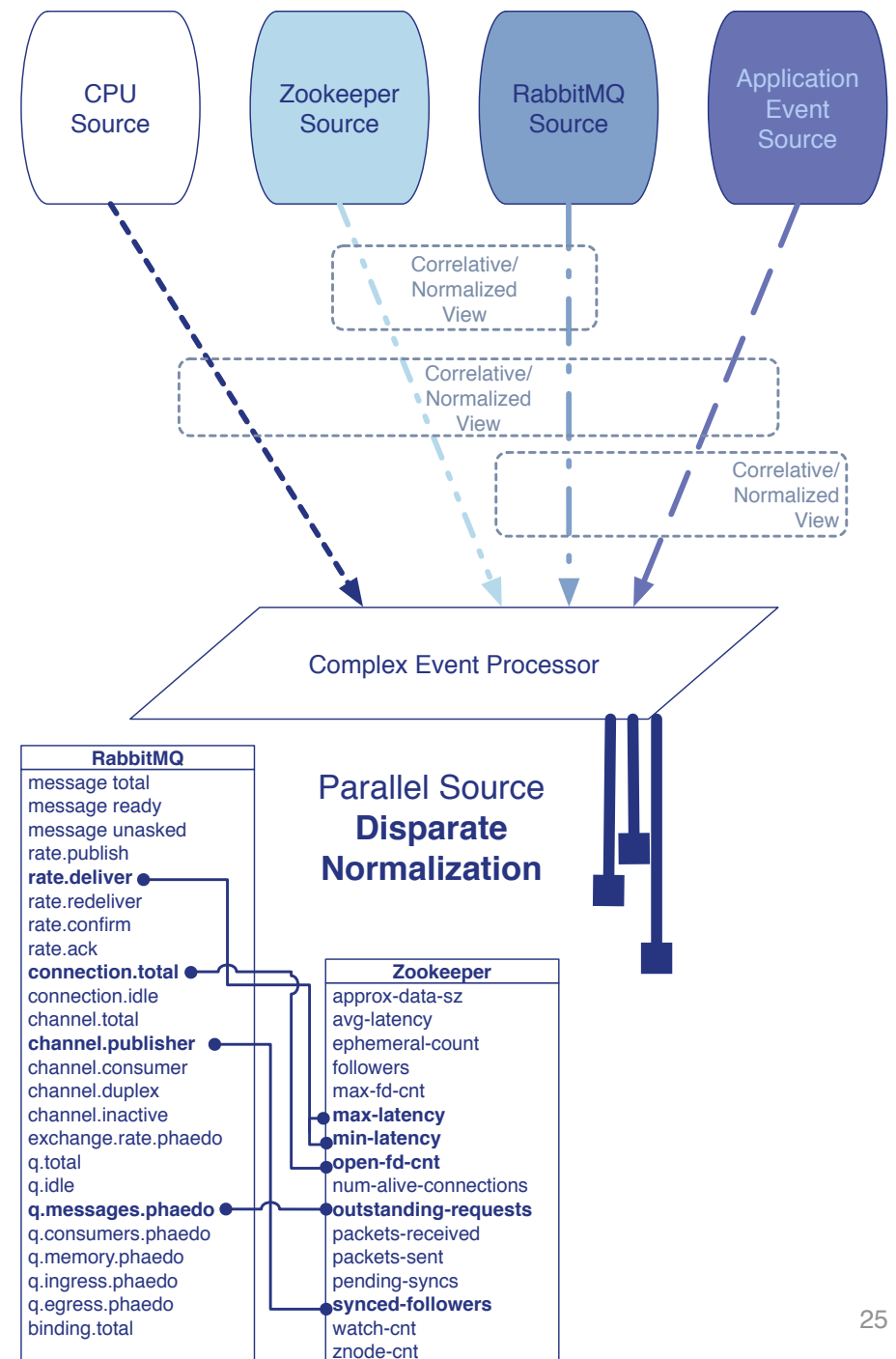
Affinity + Simple Case

Stream + Augmented Datasource

Parallel Stream

Frequency-Shifted Stream

- “Correlative/Normalized View”: Similar to a SQL “join” concept, we relate data fields in disparate stream sources
- Requires frequency mapping (sliding windows, state management, etc.)
- **Use Case Example: Messaging System and Zookeeper filesystem relationships**
 - vector time (event/observation based)
 - incoming/outgoing pipeline relationships
 - actor mapping
 - filesystem/messaging performance



Compound Approaches

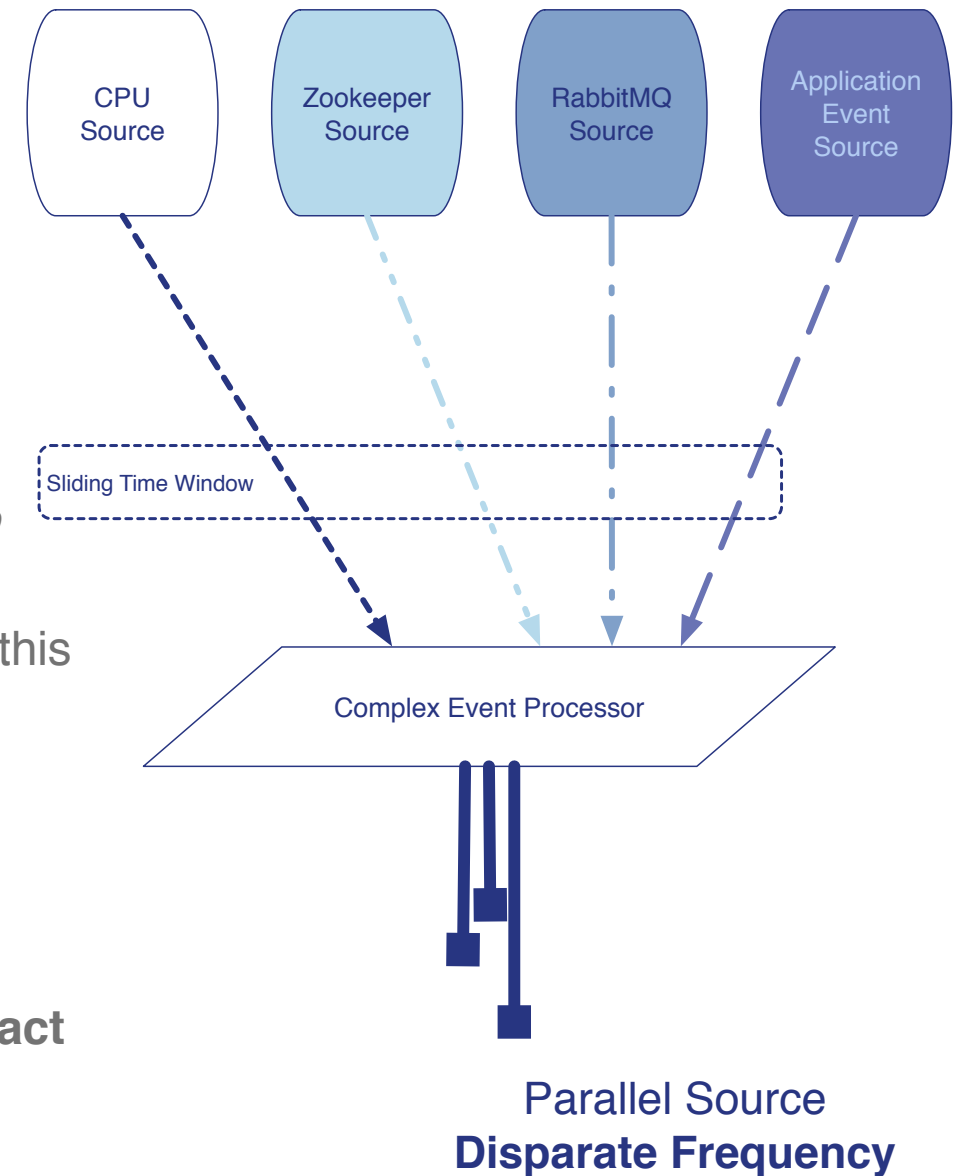
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Parallel Stream

Frequency-Shifted Stream

- Not a simple problem, and is usually where the *“it’s easier to just do this in situ”* argument comes up.
- Most sources do not publish at the same interval. To handle this we need a variety of techniques (some examples):
 - sliding time windows
 - state management (value looping)
 - relevancy-offset clocks (determined by “master events”)
 - store and forward
- **Use Case Example: Application Environmental CPU Impact**
 - CPU published on time interval, leverage value looping
 - Application is event-driven, it’s the master.



CPU	Zookeeper	RabbitMQ	Application
event_duration_ms	event_duration_ms	event_duration_ms	event_duration_ms
event_timestamp_orig	event_timestamp_orig	event_timestamp_orig	event_timestamp_orig
observed_timestamp	observed_timestamp	observed_timestamp	observed_timestamp
observation_latency	observation_latency	observation_latency	observation_latency

What does it take to get from design to best-practice?

If we take away nothing else...

Theory into Practice



Theory into Practice

In-situ is easy, but it's **not going to work long term** — we need to gain real insight faster — as things happen.



Theory into Practice

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Push analytics to the edge. We will see near-field analytics, edge-analytics, related-entity analytics, etc. **When you can't push it to the edge, push it to the edge anyway.**



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Never underestimate the power and placement of small computers. My watch is more capable than laptops only 2 generations ago. The age of **general compute** is **giving way to generally specialized** computers. They will make a huge difference to streaming larger and more complex data. We really can look at everything.

